PRESIDENCY UNIVERSITY

GAIN MORE KNOWLEDGE
REACH GREATER HEIGHTS

Laboratory Certificate

This is to certify that Mr YESHWANTH S GOWDA Register No 20201ISB0016

has satisfactorily completed the course of Experiments in DATA HANDLING AND VISUALIZATION Prescribed by the PRESIDENCY UNIVERSITY in The Laboratory of this College in the year 2023 - 2024

Signature of the Lecturer
in Charge

DATE:

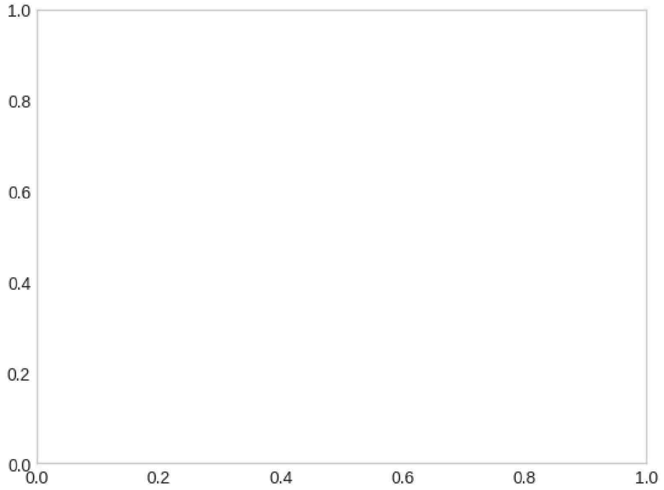
INDEX

LABSHEET 1

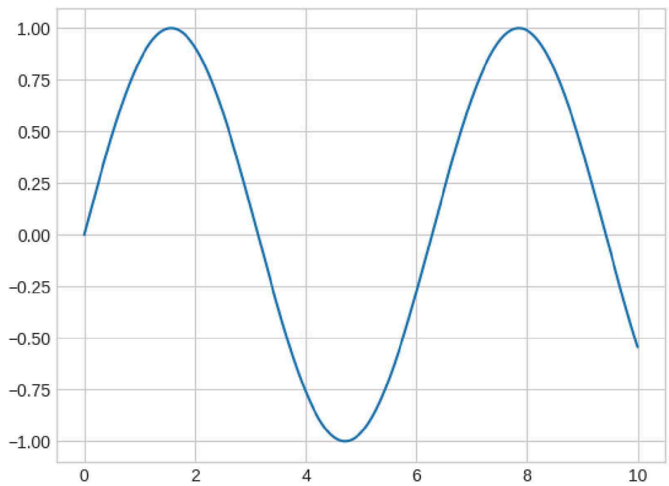
```
from matplotlib import pyplot as plt
plt.style.use('seaborn-whitegrid')

import numpy as np
print("step 1")
```

```
step 1
<ipython-input-4-240c5389bdd3>:2: MatplotlibDeprecationWarning: The seaborn styles shipped by Matplotlib are deprecated since 3.6, a
  plt.style.use('seaborn-whitegrid')
```

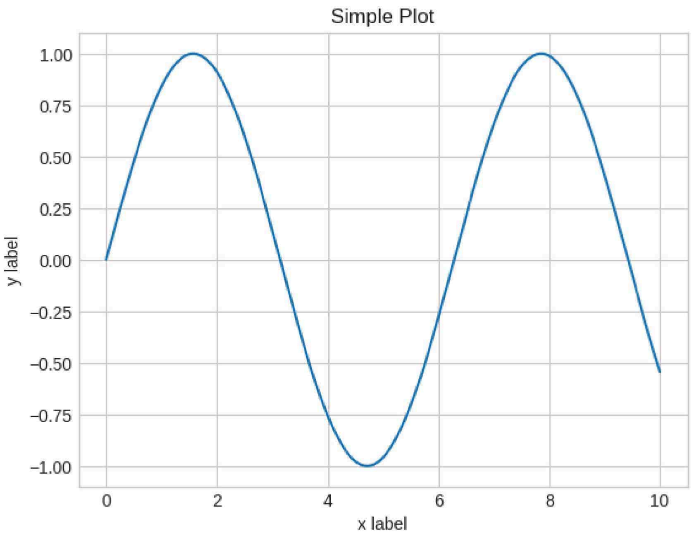
```
fig = plt.figure()
ax = plt.axes()
ax.grid()
```



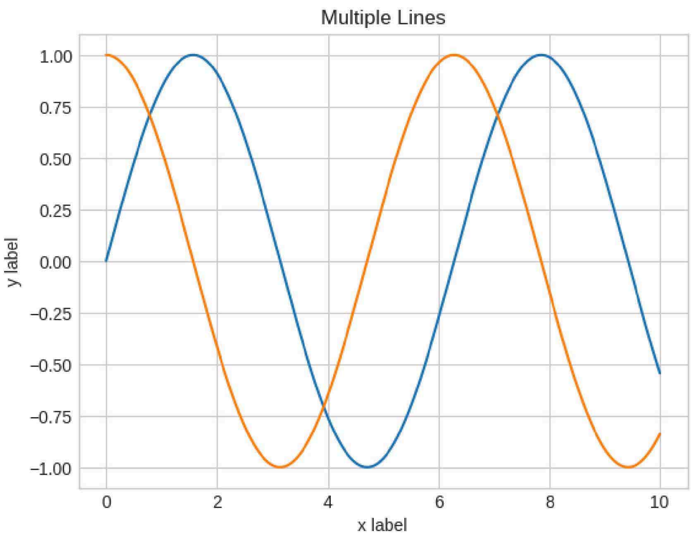

```
fig = plt.figure()
ax = plt.axes()

x = np.linspace(0, 10, 1000)
ax.plot(x, np.sin(x));
```



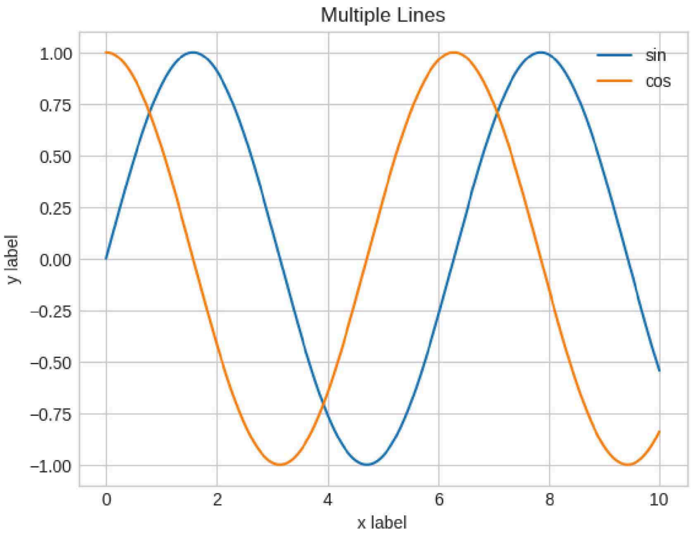
```
# Lets add a title and labels to the plot

fig = plt.figure()
ax = plt.axes()

x = np.linspace(0, 10, 1000)
ax.plot(x, np.sin(x))
ax.set_title('Simple Plot')   # Add a title
ax.set_xlabel('x label')          # Add x label
ax.set_ylabel('y label');         # Add y label
```



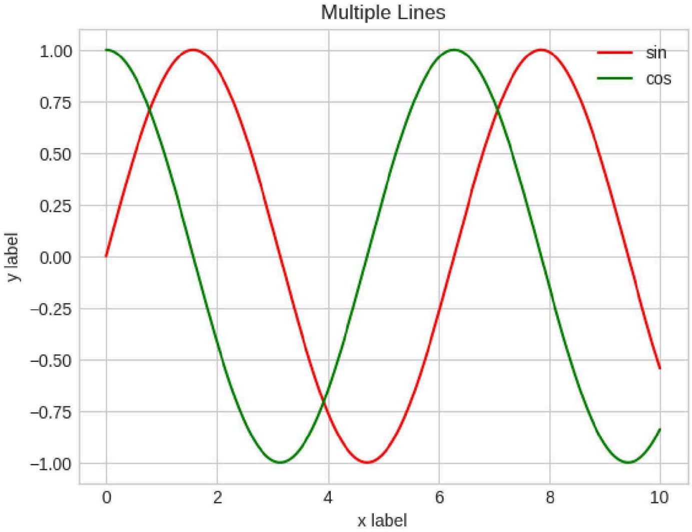

```
# Lets add a title to the plot above
fig = plt.figure()
ax = plt.axes()

x = np.linspace(0, 10, 1000)
ax.plot(x, np.sin(x))
ax.plot(x, np.cos(x))
#ax.plot(x, np.tan(x))
ax.set_title('Multiple Lines');
ax.set_xlabel('x label')
ax.set_ylabel('y label')
plt.show()
```



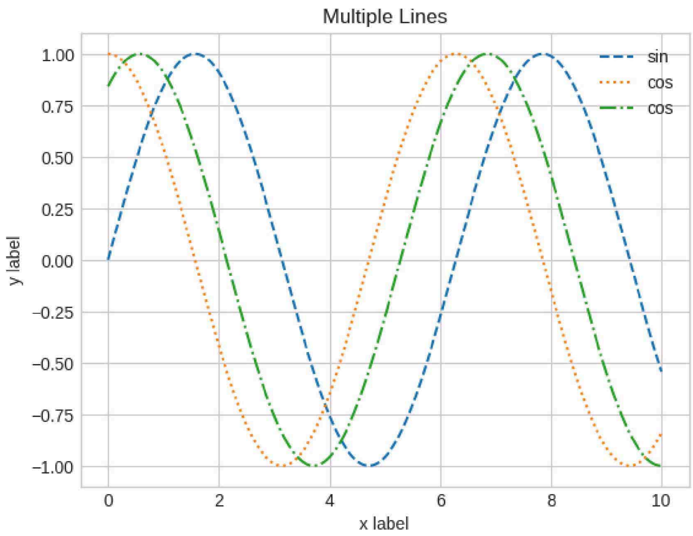
```
fig = plt.figure()
ax = plt.axes()

x = np.linspace(0, 10, 1000)
ax.plot(x, np.sin(x), label = 'sin')
ax.plot(x, np.cos(x), label = 'cos')
ax.set_title('Multiple Lines');
ax.set_xlabel('x label')
ax.set_ylabel('y label')
ax.legend()
# ax.legend(loc=1)
plt.show()
```



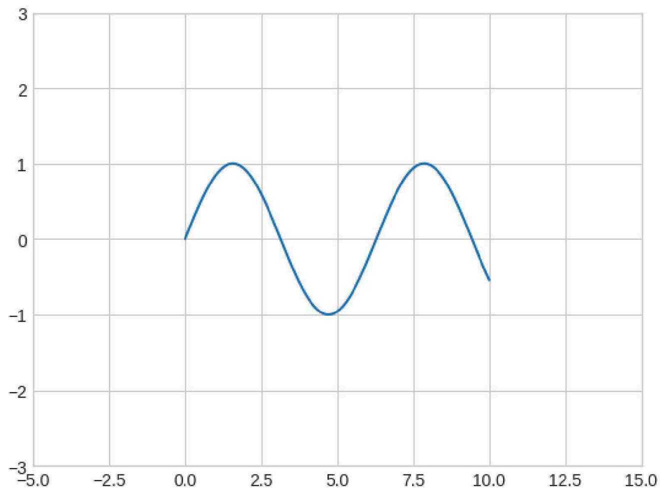

```
fig = plt.figure()
ax = plt.axes()

x = np.linspace(0, 10, 1000)
ax.plot(x, np.sin(x), label = 'sin', color = 'red')   # specify color by name
ax.plot(x, np.cos(x), label = 'cos', color = 'g')    # short color code (rgbcmyk)
ax.set_title('Multiple Lines');
ax.set_xlabel('x label')
ax.set_ylabel('y label')
ax.legend();
```



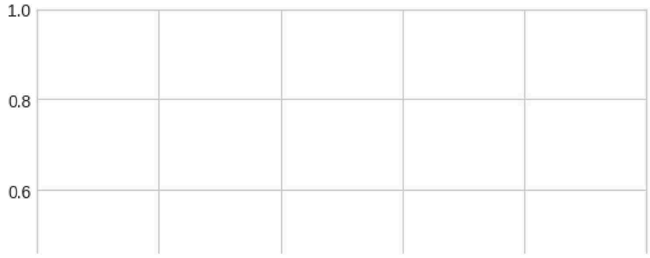
```
fig = plt.figure()
ax = plt.axes()
# ax.grid(linestyle = '--')

x = np.linspace(0, 10, 1000)
ax.plot(x, np.sin(x), label = 'sin', linestyle = 'dashed')
ax.plot(x, np.cos(x), label = 'cos', linestyle = 'dotted')
ax.plot(x, np.sin(x+1), label = 'cos', linestyle = 'dashdot')
ax.set_title('Multiple Lines');
ax.set_xlabel('x label')
ax.set_ylabel('y label')
ax.legend();
```



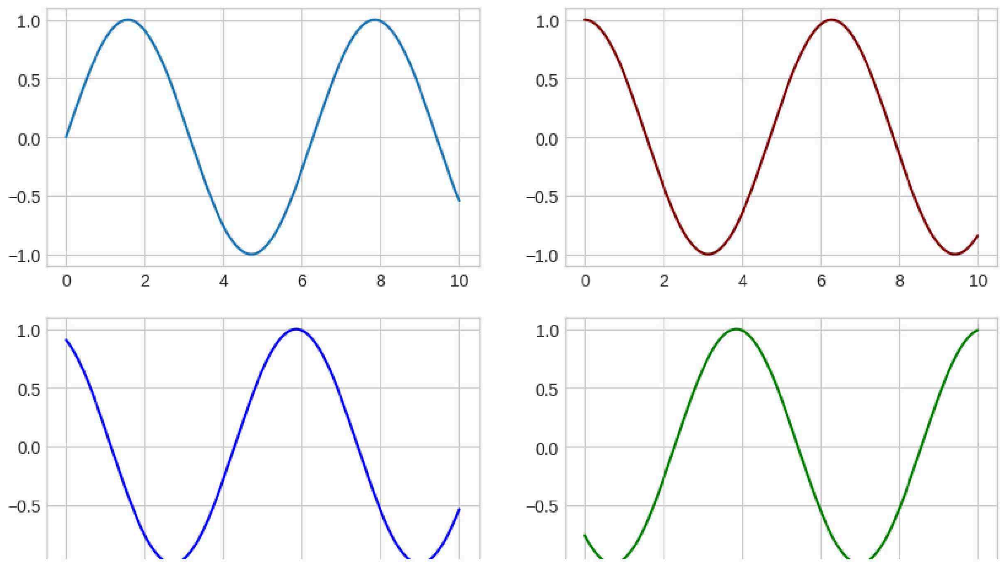

```
fig = plt.figure()
ax = plt.axes()

x = np.linspace(0, 10, 1000)
ax.plot(x, np.sin(x))

ax.set_xlim(-5, 15)
ax.set_ylim(-3, 3);
```




```
fig, ax = plt.subplots()        # a figure with a single Axes
```




```
fig, axs = plt.subplots(2, 2, figsize=(10,6)) # a figure with a 2x2 grid of Axes
x = np.linspace(0, 10, 1000)

axs[0,0].plot(x, np.sin(x))

axs[0,1].plot(x, np.cos(x), color = 'maroon')

axs[1,0].plot(x, np.sin(x+2), color = 'blue')

axs[1,1].plot(x, np.sin(x+4), color = 'green');
```



LABSHEET 2

pandas

```
import pandas as pd
data=pd.read_csv(r'C:\Users\Thejas Venugopal\Downloads\nyc_weather.csv')
data.head()
```

	EST	Temperature	DewPoint	Humidity	Sea Level PressureIn	VisibilityMiles	WindSpeedMP
0	1/1/2016	38	23	52	30.03	10	8.
1	1/2/2016	36	18	46	30.02	10	7.
2	1/3/2016	40	21	47	29.86	10	8.
3	1/4/2016	25	9	44	30.05	10	9.

pandas series

```
import numpy as np
d=np.array(['a','b','c','d'])
s=pd.Series(d)
print(s)
```

```
0    a
1    b
2    c
3    d
dtype: object
```

with d being a dictionary

```
d={'a':1.,'b':2,'c':3}
s=pd.Series(d,index=['b','c','d'])
s
```

```
b    2.0
c    3.0
d    NaN
dtype: float64
```

changing the index

```
d=np.array(['a','b','c','d'])
s=pd.Series(d,index=[100,101,102,103])
print(s)
```

```
100    a
101    b
102    c
103    d
dtype: object
```

dtype = float

```
n=np.array([1,2,3])
s1=pd.Series(n,dtype=float)
s1
```

```
0    1.0
1    2.0
2    3.0
dtype: float64
```

syntax

pd.Series(data,index=[ ],dtype=, name=, copy=,)

combining 2 arrays to make an object

```
a1=np.array([1,2,3])
a2=np.array(['a','b','z'])
s2=pd.Series(a1,a2)
s2
```

```
a    1
b    2
z    3
dtype: int32
```

handling missing values

```
d={'a':1.,'b':2,'c':3}
s=pd.Series(d,index=['b','c','d'])
print(s)
```

```
b    2.0
c    3.0
d    NaN
dtype: float64
```

```
s.isna().sum()
```

```
1
```

```
s.dropna()
```

```
b    2.0
c    3.0
dtype: float64
```

```
d={'a':1.,'b':2,'c':3}
s=pd.Series(d,index=['b','c','d'])
print(s)
```

```
b    2.0
c    3.0
d    NaN
dtype: float64
```

```
s.fillna(2)
```

```
b    2.0
c    3.0
d    2.0
dtype: float64
```

accessing elements from the index

```
series=pd.Series([1,2,3,4,5],index=['a','b','c','d','e'])
series[1]
```

```
2
```

```
series[:3]
```

```
a    1
b    2
c    3
dtype: int64
```

```
series['a']
```

```
1
```

```
series[['a','c','e']]
```

```
a    1
c    3
e    5
dtype: int64
```

```
series1=pd.Series([103,1079,978],index=[' a hundred and three','one thousand seventy nine','nine hundred seventy eight'])
series1['nine hundred seventy eight']
```

```
978
```

DATA FRAME

```
import pandas as pd
data = {'Name':['Alice', 'Bob', 'Claire', 'David'],
        'Age':[20, 21, 20, 22]}
df = pd.DataFrame(data)
print(df)
```

```
     Name  Age
0   Alice   20
1     Bob   21
2  Claire   20
3   David   22
```

```
# creating a dataframe from a list of dictionary
data = [{'Name': 'Alice', 'Age': 20},
        {'Name': 'Bob', 'Age': 21},
        {'Name': 'Claire', 'Age': 20},
        {'Name': 'David', 'Age': 22}]
df = pd.DataFrame(data)
print(df)
```

```
     Name  Age
0   Alice   20
1     Bob   21
2  Claire   20
3   David   22
```

```
pd.DataFrame(df)
```

	Name	Age
0	Alice	20
1	Bob	21
2	Claire	20
3	David	22

Start coding or generate with AI.

LABSHEET 3

Data Cleaning and Data Preprocessing:

1. Data cleaning is the process of changing or eliminating garbage, incorrect, duplicate, corrupted, or incomplete data in a dataset.
2. There's no such absolute way to describe the precise steps in the data cleaning process because the processes may vary from dataset to dataset.

Data Cleaning Cycle

Missing Values:

```
# import the pandas library
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])
print(df)
# df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

# print (df)
```

```
        one       two     three
a  0.375319 -0.763927 -0.762393
c -1.093644  1.335944 -0.668966
e -0.013401  0.155461 -0.843651
f  0.423813  0.900266 -0.828664
h -0.644593  2.654895  1.211697
```

Check for Missing Values:

To make detecting missing values easier (and across different array dtypes),Pandas provides the **isnull()** and **notnull()** functions, which are also methods on Series and DataFrame objects −

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])

df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

# print (df['one'].isnull())
# print(df)
print(df["one"].isnull())
```

```
a    False
b     True
c    False
d     True
e    False
f    False
g     True
h    False
Name: one, dtype: bool
```

Replacing the Missing Values

```
#Replace the missing values by 0
import pandas as pd
import numpy as np
df = pd.DataFrame(np.random.randn(3, 3), index=['a', 'c', 'e'],columns=['one',
'two', 'three'])
df = df.reindex(['a', 'b', 'c'])
print (df)
print ("NaN replaced with '0':")
print (df.fillna(0))
```

```
        one       two     three
a -0.961858 -1.671248  0.556286
b       NaN       NaN       NaN
c -0.386504 -0.709324  0.622838
NaN replaced with '0':
        one       two     three
a -0.961858 -1.671248  0.556286
b  0.000000  0.000000  0.000000
c -0.386504 -0.709324  0.622838
```

Fill NA Forward and Backward

```
# Method           Action
pad/fill          Fill methods Forward
bfill/backfill    Fill methods Backward
```

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])
df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
print(df)
print (df.fillna(method='pad'))
```

```
        one       two     three
a  0.109813 -1.940379 -0.444834
b       NaN       NaN       NaN
c -0.208020  0.309864  0.819870
d       NaN       NaN       NaN
e -0.465764  0.215614  1.031519
f  1.189843  3.814140  0.954030
g       NaN       NaN       NaN
h  0.480653  0.552598 -0.888482
        one       two     three
a  0.109813 -1.940379 -0.444834
b  0.109813 -1.940379 -0.444834
c -0.208020  0.309864  0.819870
d -0.208020  0.309864  0.819870
e -0.465764  0.215614  1.031519
f  1.189843  3.814140  0.954030
g  1.189843  3.814140  0.954030
h  0.480653  0.552598 -0.888482
```

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])
df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])

print (df.fillna(method='bfill'))
```

```
        one       two     three
a -1.204446  2.137228 -0.388020
b  1.327178  2.355456 -1.347412
c  1.327178  2.355456 -1.347412
d -0.228600  1.300295  0.939832
e -0.228600  1.300295  0.939832
f -0.938383  2.278881 -0.098408
g  0.726762  0.456629 -1.167753
h  0.726762  0.456629 -1.167753
```

Drop Missing Values:

Use dropna function along with the axis argument.
By default, axis=0, i.e., along row, which means that if any value within a row is NA then the whole row is excluded.

```
import pandas as pd
import numpy as np

df = pd.DataFrame(np.random.randn(5, 3), index=['a', 'c', 'e', 'f',
'h'],columns=['one', 'two', 'three'])
print(df)
df = df.reindex(['a', 'b', 'c', 'd', 'e', 'f', 'g', 'h'])
print(df)
print (df.dropna())
```

```
        one       two     three
a -0.481989 -1.249458 -2.316982
c  1.119240 -1.054186 -0.972090
e -0.991040 -0.749165  0.259387
f -1.300768 -0.000567 -0.056870
h  0.497341  0.984014 -1.094049
        one       two     three
a -0.481989 -1.249458 -2.316982
b       NaN       NaN       NaN
c  1.119240 -1.054186 -0.972090
d       NaN       NaN       NaN
e -0.991040 -0.749165  0.259387
f -1.300768 -0.000567 -0.056870
g       NaN       NaN       NaN
h  0.497341  0.984014 -1.094049
        one       two     three
a -0.481989 -1.249458 -2.316982
c  1.119240 -1.054186 -0.972090
e -0.991040 -0.749165  0.259387
f -1.300768 -0.000567 -0.056870
h  0.497341  0.984014 -1.094049
```

Replace Missing (or) Generic Values:

We can achieve this by applying the **replace** method.

Replacing NA with a scalar value is equivalent behavior of the **fillna()** function.

```
import pandas as pd
import numpy as np
df = pd.DataFrame({'one':[10,20,30,40,50,2000],
'two':[1000,0,30,40,50,60]})
print(df)
print (df.replace({1000:10,2000:60}))
```

```
    one   two
0    10  1000
1    20     0
2    30    30
3    40    40
4    50    50
5  2000    60
   one  two
0   10   10
1   20    0
2   30   30
3   40   40
```

```
4   50   50
5   60   60
```

Data Preprocessing

1. Load data in Pandas
2. Drop columns that aren’t useful
3. Drop rows with missing values
4. Create dummy variables
5. Take care of missing data
6. Convert the data frame to NumPy

Download Titanic-Dataset from Kaggle.com.
Here we are going to use train.csv dataset for preprocessing.

```
import pandas as pd
import numpy as np
from google.colab import drive
drive.mount('/content/drive')
```

```
Mounted at /content/drive
```

```
df = pd.read_csv(r"C:\Users\Thejas Venugopal\Downloads\train (1).csv")
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 891 entries, 0 to 890
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  891 non-null    int64
 1   Survived     891 non-null    int64
 2   Pclass       891 non-null    int64
 3   Name         891 non-null    object
 4   Sex          891 non-null    object
 5   Age          714 non-null    float64
 6   SibSp        891 non-null    int64
 7   Parch        891 non-null    int64
 8   Ticket       891 non-null    object
 9   Fare         891 non-null    float64
 10  Cabin        204 non-null    object
 11  Embarked     889 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 83.7+ KB
```

Drop the Columns that are not required

```
cols=['Name','Ticket','Cabin']
df=df.drop(cols,axis=0)
df.info()
```

```
---------------------------------------------------------------------------
KeyError                                  Traceback (most recent call last)
C:\Users\THEJAS~1\AppData\Local\Temp/ipykernel_20436/1019933480.py in <module>
      1 cols=['Name','Ticket','Cabin']
----> 2 df=df.drop(cols)
      3 df.info()

c:\Users\Thejas Venugopal\anaconda3\lib\site-packages\pandas\util\_decorators.py in
wrapper(*args, **kwargs)
    309                     stacklevel=stacklevel,
    310                 )
--> 311             return func(*args, **kwargs)
    312 
    313         return wrapper

c:\Users\Thejas Venugopal\anaconda3\lib\site-packages\pandas\core\frame.py in
drop(self, labels, axis, index, columns, level, inplace, errors)
   4904                 weight  1.0     0.8
   4905         """
-> 4906         return super().drop(
   4907             labels=labels,
   4908             axis=axis,

c:\Users\Thejas Venugopal\anaconda3\lib\site-packages\pandas\core\generic.py in
drop(self, labels, axis, index, columns, level, inplace, errors)
   4148         for axis, labels in axes.items():
   4149             if labels is not None:
-> 4150                 obj = obj._drop_axis(labels, axis, level=level,
errors=errors)
   4151 
   4152         if inplace:

c:\Users\Thejas Venugopal\anaconda3\lib\site-packages\pandas\core\generic.py in
_drop_axis(self, labels, axis, level, errors)
   4183                 new_axis = axis.drop(labels, level=level, errors=errors)
   4184             else:
-> 4185                 new_axis = axis.drop(labels, errors=errors)
   4186             result = self.reindex(**{axis_name: new_axis})
   4187 

c:\Users\Thejas Venugopal\anaconda3\lib\site-packages\pandas\core\indexes\base.py in
drop(self, labels, errors)
   6015         if mask.any():
   6016             if errors != "ignore":
-> 6017                 raise KeyError(f"{labels[mask]} not found in axis")
```

Drop the rows having no values

```
df = df.dropna()
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 712 entries, 0 to 890
Data columns (total 9 columns):
```

```
 #   Column       Non-Null Count  Dtype  
---  ------       --------------  -----  
 0   PassengerId  712 non-null    int64  
 1   Survived     712 non-null    int64  
 2   Pclass       712 non-null    int64  
 3   Sex          712 non-null    object 
 4   Age          712 non-null    float64
 5   SibSp        712 non-null    int64  
 6   Parch        712 non-null    int64  
 7   Fare         712 non-null    float64
 8   Embarked     712 non-null    object 
dtypes: float64(2), int64(5), object(2)
memory usage: 55.6+ KB
```

Creating Dummy variables

Instead of wasting our data, let's convert the Pclass, Sex and Embarked to columns in Pandas and drop them after conversion.

```
dummies = []
cols = ['Pclass', 'Sex', 'Embarked']
for col in cols:
   dummies.append(pd.get_dummies(df[col]))
```

Transfor the eigth columns

```
titanic_dummies = pd.concat(dummies, axis=1)
```

Concatenate the values with data frame

```
df = pd.concat((df,titanic_dummies), axis=1)
```

Remove the unwanted cols

```
df = df.drop(['Pclass', 'Sex', 'Embarked'], axis=1)
```

Take care of Missing data

Let's compute a **median or interpolate()** all the ages and fill those missing age values. Pandas has an interpolate() function that will replace all the missing NaNs to interpolated values.

```
df['Age'] = df['Age'].interpolate()
print(df)
```

Min Max Scaler and Standardization

Normalization is a rescaling of the data from the original range so that all values are within the new range of 0 and 1.

A value is normalized as follows:

y = (x – min) / (max – min)

```
from sklearn.preprocessing import MinMaxScaler
data = [[-1, 2], [-0.5, 6], [0, 10], [1, 18]]
scaler = MinMaxScaler()
print(scaler.fit(data))
MinMaxScaler()
print(scaler.data_max_)
print(scaler.transform(data))
```

```
MinMaxScaler()
[ 1. 18.]
[[0.   0.  ]
 [0.25 0.25]
 [0.5  0.5 ]
 [1.   1.  ]]
```

Data Standardization

Standardizing a dataset involves rescaling the distribution of values so that the mean of observed values is 0 and the standard deviation is 1.

A value is standardized as follows:

y = (x – mean) / standard_deviation

Where the mean is calculated as:

mean = sum(x) / count(x)

And the standard_deviation is calculated as:

standard_deviation = sqrt(sum((x – mean)^2) / count(x))

```
from numpy import asarray
from sklearn.preprocessing import StandardScaler
# define data
data = asarray([[100, 0.001],
 [8, 0.05],
 [50, 0.005],
 [88, 0.07],
 [4, 0.1]])
print(data)
# define standard scaler
scaler = StandardScaler()
# transform data
scaled = scaler.fit transform(data)
```

LABSHEET 4

```
import numpy as np
import pandas as pd
```

```
# Example dataset
data = {
    'Feature1': [10, 20, 30, 40, 50],
    'Feature2': [5, 15, 25, 35, 45]
}

# Create a DataFrame
df = pd.DataFrame(data)

# Display the original data
print("Original Data:")
print(df)
```

```
Original Data:
   Feature1  Feature2
0        10         5
1        20        15
2        30        25
3        40        35
4        50        45
```

```
# Function to normalize data using Z-score
def zscore_normalization(df):
    normalized_df = df.copy()
    for column in normalized_df.columns:
        mean = normalized_df[column].mean()
        std = normalized_df[column].std()
        normalized_df[column] = (normalized_df[column] - mean) / std
    return normalized_df

# Normalize the DataFrame
normalized_df = zscore_normalization(df)

# Display the normalized data
print("\nNormalized Data (Z-score):")
print(normalized_df)
```

```

Normalized Data (Z-score):
   Feature1  Feature2
0 -1.264911 -1.264911
1 -0.632456 -0.632456
2  0.000000  0.000000
3  0.632456  0.632456
4  1.264911  1.264911
```

LABSHEET 5

```
from google.colab import files
df = files.upload()
```

Choose Files No file chosen Upload widget is only available when the cell has been executed in the current browser session. Please rerun this cell to enable.

```
Saving train.csv to train.csv
```

```
import pandas as pd
import numpy as np
```

```
data = pd.read_csv('./train.csv')
data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	493	0	1	Molson, Mr. Harry Markland	male	55.0	0	0	113787	30.5000	C30	S
1	53	1	1	Harper, Mrs. Henry Sleeper (Myna Haxtun)	female	49.0	1	0	PC 17572	76.7292	D33	C
2	388	1	2	Buss, Miss. Kate	female	36.0	0	0	27849	13.0000	NaN	S
3	192	0	2	Carbines, Mr. William	male	19.0	0	0	28424	13.0000	NaN	S
4	687	0	3	Panula, Mr. Jaako Arnold	male	14.0	4	1	3101295	39.6875	NaN	S

```
cols = ['Name', 'Ticket', 'Cabin']
filtered_data = data.drop(cols, axis = 1)
filtered_data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 712 entries, 0 to 711
Data columns (total 9 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  712 non-null    int64
 1   Survived     712 non-null    int64
 2   Pclass       712 non-null    int64
 3   Sex          712 non-null    object
 4   Age          566 non-null    float64
 5   SibSp        712 non-null    int64
 6   Parch        712 non-null    int64
 7   Fare         712 non-null    float64
 8   Embarked     710 non-null    object
dtypes: float64(2), int64(5), object(2)
memory usage: 50.2+ KB
```

```
data = data.dropna()
data.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 148 entries, 0 to 695
Data columns (total 12 columns):
 #   Column       Non-Null Count  Dtype
---  ------       --------------  -----
 0   PassengerId  148 non-null    int64
 1   Survived     148 non-null    int64
 2   Pclass       148 non-null    int64
 3   Name         148 non-null    object
 4   Sex          148 non-null    object
 5   Age          148 non-null    float64
 6   SibSp        148 non-null    int64
 7   Parch        148 non-null    int64
 8   Ticket       148 non-null    object
 9   Fare         148 non-null    float64
 10  Cabin        148 non-null    object
 11  Embarked     148 non-null    object
dtypes: float64(2), int64(5), object(5)
memory usage: 15.0+ KB
```

```
data.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	493	0	1	Molson, Mr. Harry Markland	male	55.0	0	0	113787	30.5000	C30	S
1	53	1	1	Harper, Mrs. Henry Sleeper (Myna Haxtun)	female	49.0	1	0	PC 17572	76.7292	D33	C
9	752	1	3	Moor, Master. Meier	male	6.0	0	1	392096	12.4750	E121	S
10	541	1	1	Crosby, Miss. Harriet R	female	36.0	0	2	WE/P 5735	71.0000	B22	S

```
dummies = []
cols = ['Pclass', 'Sex', 'Embarked']
for col in cols:
  dummies.append(pd.get_dummies(data[col]))
```

```
dummies
```

```
[     1  2  3
 0    1  0  0
 1    1  0  0
 2    0  1  0
 3    0  1  0
 4    0  0  1
 ..  .. .. ..
 707  0  0  1
 708  1  0  0
 709  0  0  1
 710  0  1  0
 711  1  0  0

 [712 rows x 3 columns],
      female  male
 0         0     1
 1         1     0
 2         1     0
 3         0     1
 4         0     1
 ..      ...   ...
 707       1     0
 708       0     1
 709       0     1
 710       0     1
 711       0     1

 [712 rows x 2 columns],
      C  Q  S
 0    0  0  1
 1    1  0  0
 2    0  0  1
 3    0  0  1
 4    0  0  1
 ..  .. .. ..
 707  1  0  0
 708  1  0  0
 709  0  0  1
 710  0  0  1
 711  0  0  1

 [712 rows x 3 columns]]
```

```
titanic_dummies = pd.concat(dummies, axis = 1)
titanic_dummies
```

	1	2	3	female	male	C	Q	S
0	1	0	0	0	1	0	0	1
1	1	0	0	1	0	1	0	0
2	0	1	0	1	0	0	0	1
3	0	1	0	0	1	0	0	1
4	0	0	1	0	1	0	0	1
...	...	...	...	...	...	...	...	...
707	0	0	1	1	0	1	0	0
708	1	0	0	0	1	1	0	0
709	0	0	1	0	1	0	0	1
710	0	1	0	0	1	0	0	1
711	1	0	0	0	1	0	0	1

712 rows × 8 columns

```
data.drop(['Pclass', 'Sex', 'Embarked'], axis = 1)
```

	PassengerId	Survived	Name	Age	SibSp	Parch	Ticket	Fare	Cabin
0	493	0	Molson, Mr. Harry Markland	55.0	0	0	113787	30.5000	C30
1	53	1	Harper, Mrs. Henry Sleeper (Myna Haxtun)	49.0	1	0	PC 17572	76.7292	D33
2	388	1	Buss, Miss. Kate	36.0	0	0	27849	13.0000	NaN
3	192	0	Carbines, Mr. William	19.0	0	0	28424	13.0000	NaN
4	687	0	Panula, Mr. Jaako Arnold	14.0	4	1	3101295	39.6875	NaN
...	...	...	...	...	...	...	...	...	...
707	859	1	Baclini, Mrs. Solomon (Latifa Qurban)	24.0	0	3	2666	19.2583	NaN
708	65	0	Stewart, Mr. Albert A	NaN	0	0	PC 17605	27.7208	NaN
709	130	0	Ekstrom, Mr. Johan	45.0	0	0	347061	6.9750	NaN
710	21	0	Fynney, Mr. Joseph J	35.0	0	0	239865	26.0000	NaN
711	476	0	Clifford, Mr. George Quincy	NaN	0	0	110465	52.0000	A14

712 rows × 9 columns

```
data['Age'] = data['Age'].interpolate()
print(data)
```

```
     PassengerId  Survived  Pclass                                     Name  \
0            493         0       1               Molson, Mr. Harry Markland
1             53         1       1  Harper, Mrs. Henry Sleeper (Myna Haxtun)
2            388         1       2                         Buss, Miss. Kate
3            192         0       2                    Carbines, Mr. William
4            687         0       3                 Panula, Mr. Jaako Arnold
..           ...       ...     ...                                      ...
707          859         1       3     Baclini, Mrs. Solomon (Latifa Qurban)
708           65         0       1                    Stewart, Mr. Albert A
709          130         0       3                       Ekstrom, Mr. Johan
710           21         0       2                     Fynney, Mr. Joseph J
711          476         0       1               Clifford, Mr. George Quincy

        Sex   Age  SibSp  Parch    Ticket     Fare Cabin Embarked
0      male  55.0      0      0    113787  30.5000   C30        S
1    female  49.0      1      0  PC 17572  76.7292   D33        C
2    female  36.0      0      0     27849  13.0000   NaN        S
3      male  19.0      0      0     28424  13.0000   NaN        S
4      male  14.0      4      1   3101295  39.6875   NaN        S
..      ...   ...    ...    ...       ...      ...   ...      ...
707  female  24.0      0      3      2666  19.2583   NaN        C
708    male  34.5      0      0  PC 17605  27.7208   NaN        C
709    male  45.0      0      0    347061   6.9750   NaN        S
710    male  35.0      0      0    239865  26.0000   NaN        S
711    male  35.0      0      0    110465  52.0000   A14        S

[712 rows x 12 columns]
```

```
from sklearn.preprocessing import MinMaxScaler
data = [[-1, 1], [-0.5, 6], [0, 10], [1, 10]]
scaler = MinMaxScaler()
print(scaler.fit(data))
print(scaler.data_max_)
print(scaler.transform(data))
```

```
MinMaxScaler()
[ 1. 10.]
[[0.         0.        ]
 [0.25       0.55555556]
 [0.5        1.        ]
 [1.         1.        ]]
```

LABSHEET 6

```
import matplotlib.pyplot as plt
# import seaborn as sn

# print a empty figure
# linespace 10 points with 1000 data points
# styles
# sin x and cos x
# legend values, colors, setting x, y title and other stuff
# line styles (different styles for each line)
# setting access limits (interval limits)
# subplot (printing multiple plots)
# 0 1 y = sin and then 0 1 x = sin
```

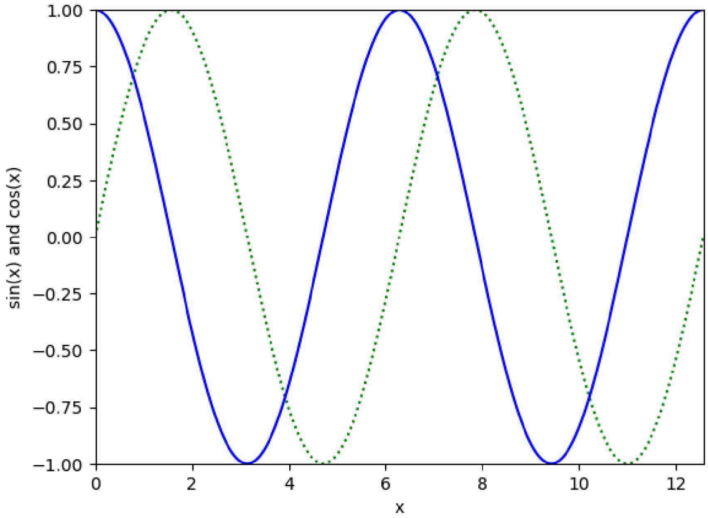
+ Code + Text

```
# print a empty figure
fig = plt.figure()
plt.show()
```

```
<Figure size 640x480 with 0 Axes>
```

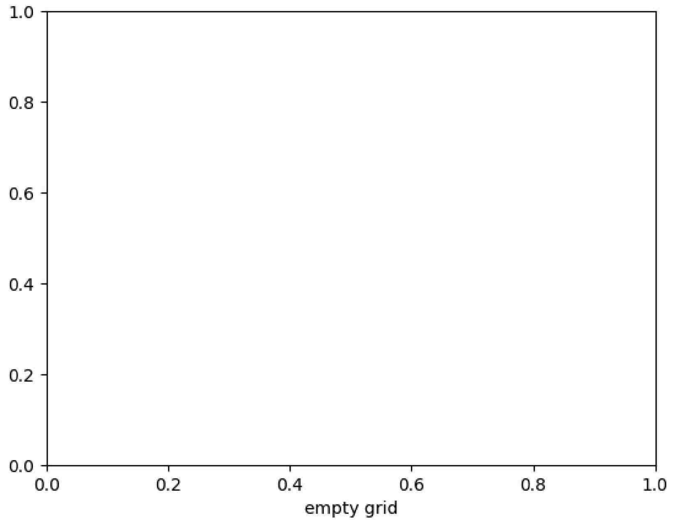
```
# print sin wave until 4pi

import numpy as np

x = np.linspace(0, 4*np.pi, 1000)
y = np.sin(x)
z = np.cos(x)
a = np.tan(x)

plt.plot(x, y, color="green", linestyle="dotted")
plt.plot(x, z, color="blue")

# Set the x-axis and y-axis limits
plt.xlim(0, 4*np.pi)
plt.ylim(-1, 1)

# Set the x-axis and y-axis labels
plt.xlabel('x')
plt.ylabel('sin(x) and cos(x)')

# Show the plot
# plt.show()
```

```
Text(0, 0.5, 'sin(x) and cos(x)')
```

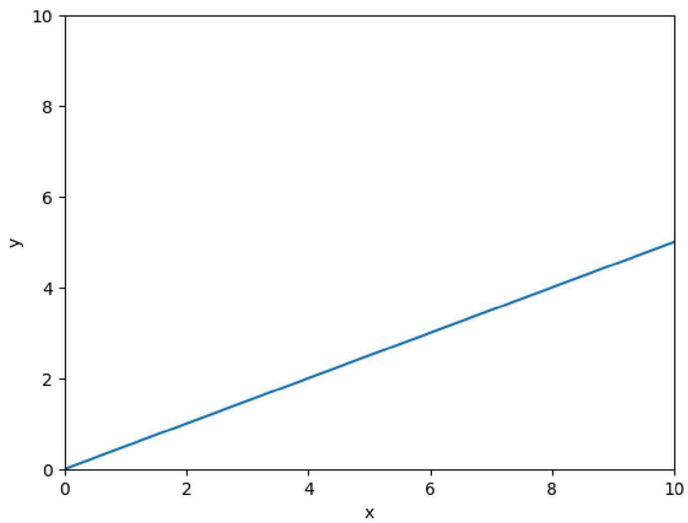



```
plt.xlabel('empty grid')
```

```
Text(0.5, 0, 'empty grid')
```

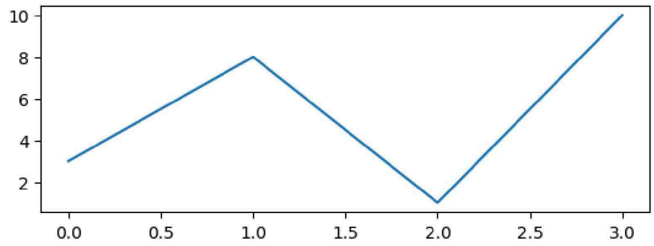



```
x = np.linspace(0, 10, 1000)
y = np.linspace(0, 5, 1000)
# plt.plot(np.sin(x), np.cos(y))
plt.plot(x, y)

# Set the x-axis and y-axis limits
plt.xlim(0, 10)
plt.ylim(0, 10)

# Set the x-axis and y-axis labels
plt.xlabel('x')
plt.ylabel('y')

# Show the plot
plt.show()
```

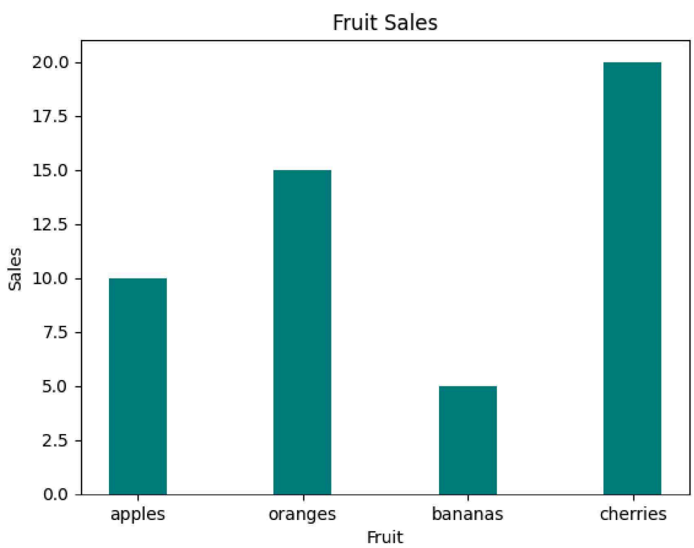



```
# printing a subplot
x = np.array([0, 1, 2, 3])
y = np.array([3, 8, 1, 10])

plt.subplot(2, 1, 1)
plt.plot(x,y)

#plot 2:
#x = np.array([0, 1, 2, 3])
#y = np.array([10, 20, 30, 40])

#plt.subplot(2, 1, 2)
#plt.plot(x,y)
```

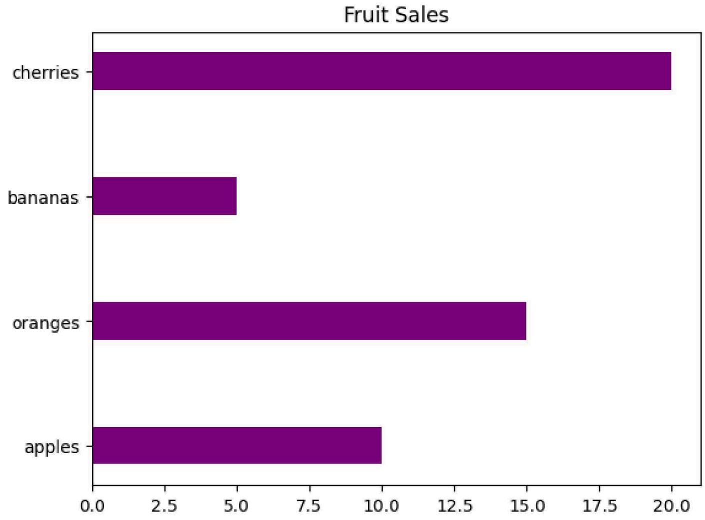
```
[<matplotlib.lines.Line2D at 0x7a4d87f00ca0>]
```




```python
# barchar example with dictionary
import matplotlib.pyplot as plt

# Define the data
data = {'apples': 10, 'oranges': 15, 'bananas': 5, 'cherries': 20}

# Create a bar chart
plt.bar(list(data.keys()), list(data.values()), width=0.35, color="teal")

# Add title and axis labels
plt.title('Fruit Sales')
plt.xlabel('Fruit')
plt.ylabel('Sales')

# Show the plot
plt.show()
```

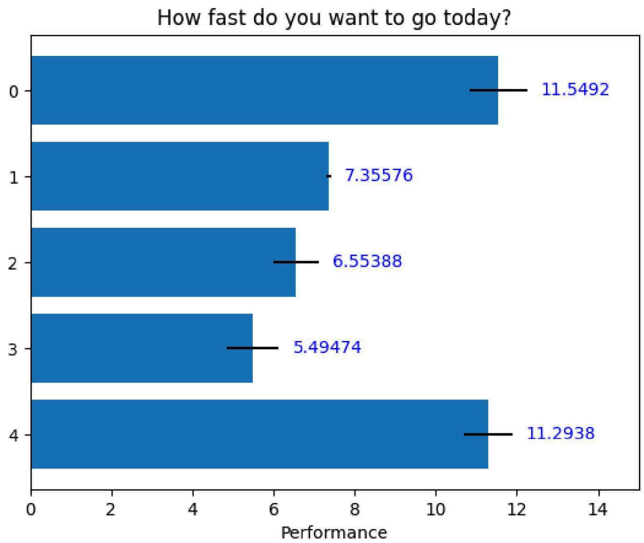



```python
# example of horizontal barchart with dictionary

# Define the data
data = {'apples': 10, 'oranges': 15, 'bananas': 5, 'cherries': 20}

# Create a horizontal bar chart
plt.barh(list(data.keys()), list(data.values()), color="purple", height=0.3)

# Add title and axis labels
plt.title('Fruit Sales')
# plt.xlabel('Sales')
# plt.ylabel('Fruit')

# Show the plot
show_plot = plt.show()
```




```
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
<ipython-input-56-dbd46437747f> in <cell line: 16>()
     14 # Show the plot
     15 show_plot = plt.show()
---> 16 show_plot.set_xlabel('something')

AttributeError: 'NoneType' object has no attribute 'set_xlabel'
```

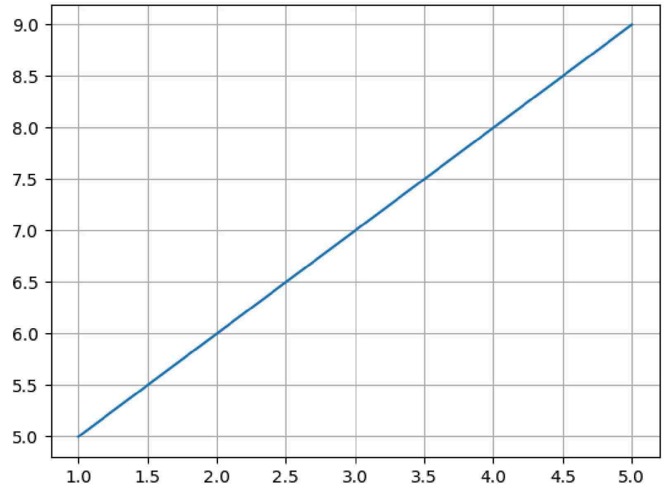
```
fig, ax = plt.subplots()

# Example data
people = ('Tom', 'Thejas', 'Harry', 'Slim', 'Jim')
y_pos = np.arange(len(people))
performance = 3 + 10 * np.random.rand(len(people))
error = np.random.rand(len(people))

hbars = ax.barh(y_pos, performance, xerr=error, align='center')
ax.invert_yaxis()
ax.set_xlabel('Performance')
ax.set_title('How fast do you want to go today?')

# Label with given captions, custom padding and annotate options
ax.bar_label(hbars, padding=8, color='b')
ax.set_xlim(right=15)

plt.show()
```




```
print(np.arange(10, 20, 2))
```

```
[10 12 14 16 18]
```

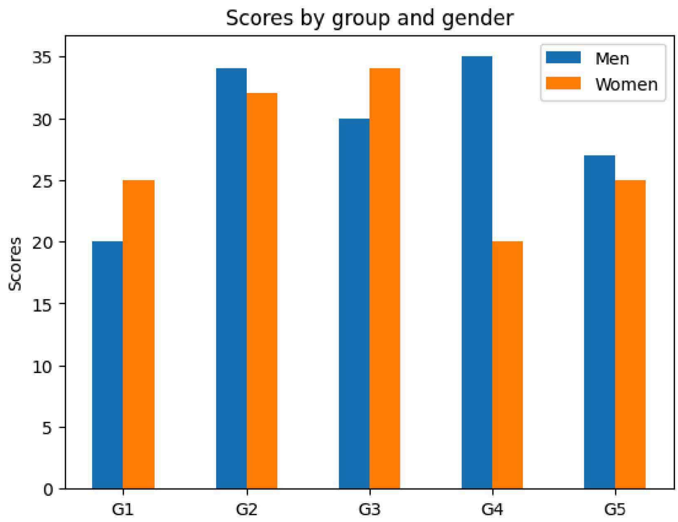
```
# pprint a axis plot with ax.grid()

import matplotlib.pyplot as plt

# Create a figure and an axes object
ax = plt.subplot()

# Plot some data
ax.plot([1, 2, 3, 4, 5], [5,6,7,8,9])

# Enable the grid
ax.grid(True)

# Show the plot
plt.show()
```



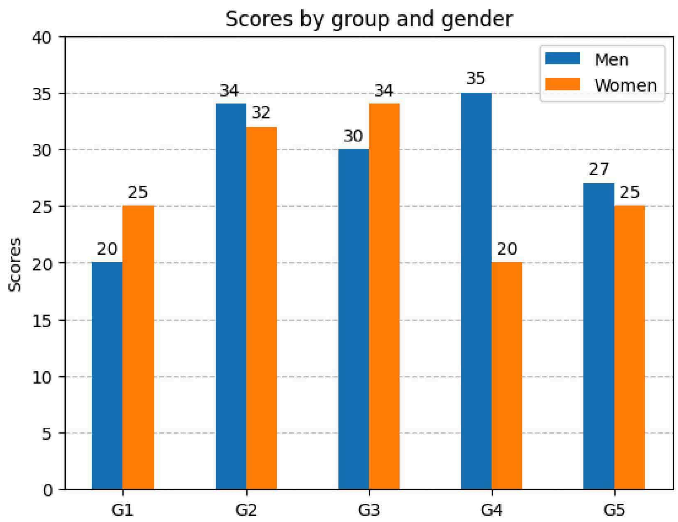

```
print(np.arange(10, 20, 2))
```

```
[10 12 14 16 18]
```

```
# grouped bar charts example
import numpy as np
import matplotlib.pyplot as plt
labels = ['G1', 'G2', 'G3', 'G4', 'G5']
men_means = [20, 34, 30, 35, 27]
women_means = [25, 32, 34, 20, 25]

x = np.arange(len(labels))
# width of the individual component
width = 0.25

fig, ax = plt.subplots()
rects1 = ax.bar(x - width/2, men_means, width, label='Men')
rects2 = ax.bar(x + width/2, women_means, width, label='Women')

# Add some text for labels, title and custom x-axis tick labels, etc.
ax.set_ylabel('Scores')
ax.set_title('Scores by group and gender')
ax.set_xticks(x)
ax.set_xticklabels(labels)
ax.legend();

plt.show()
```

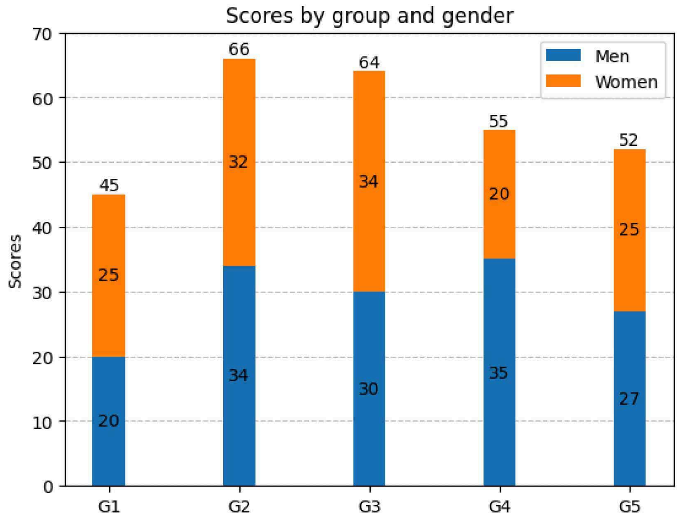



```
# adding labels to individual bars with their scores

fig, ax = plt.subplots()
ax.grid(linestyle='--', color='0.75', axis = 'y')
ax.set_axisbelow(True)

rects1 = ax.bar(x - width/2, men_means, width, label='Men')
rects2 = ax.bar(x + width/2, women_means, width, label='Women')

ax.set_ylabel('Scores')
ax.set_title('Scores by group and gender')
ax.set_xticks(x)
ax.set_xticklabels(labels)

ax.legend()

# Adding the bar labels
ax.bar_label(rects1, padding=3)
ax.bar_label(rects2, padding=3)

ax.set_ylim(0,40);
```



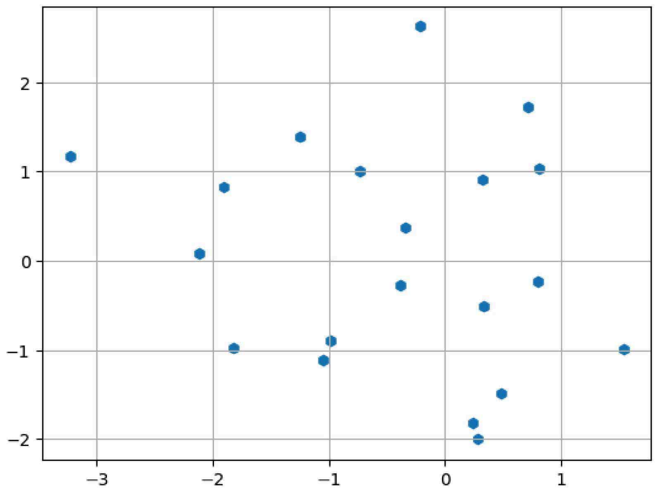
```
fig, ax = plt.subplots()
ax.grid(linestyle='--', color='0.75', axis = 'y');

ax.set_axisbelow(True) # set this to true for enabling gridlines

p1 = ax.bar(labels, men_means, width, label='Men')
p2 = ax.bar(labels, women_means, width, bottom=men_means,
       label='Women')

ax.set_ylabel('Scores')
ax.set_title('Scores by group and gender')
ax.legend()

# Label with label_type 'center'
ax.bar_label(p1, label_type='center')
ax.bar_label(p2, label_type='center')
ax.bar_label(p2)
ax.set_ylim(0,70)
```

```
(0.0, 70.0)
```

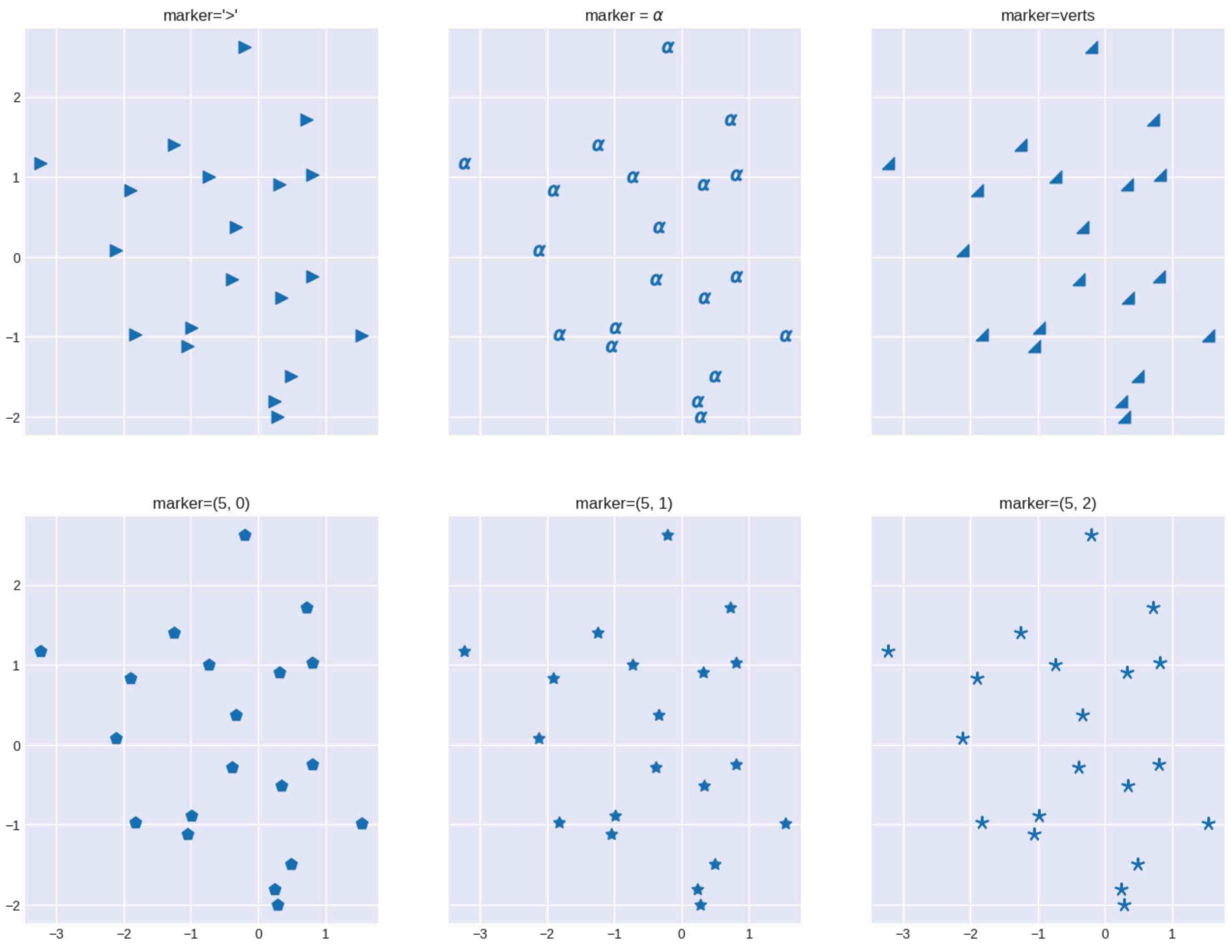



```
# scatter plot
x = np.random.randn(20)
y = np.random.randn(20)

fig, ax = plt.subplots()
ax.grid(True)
ax.scatter(x, y, marker = 'h') # can change to any marker
```

```
<matplotlib.collections.PathCollection at 0x7b29651475e0>
```

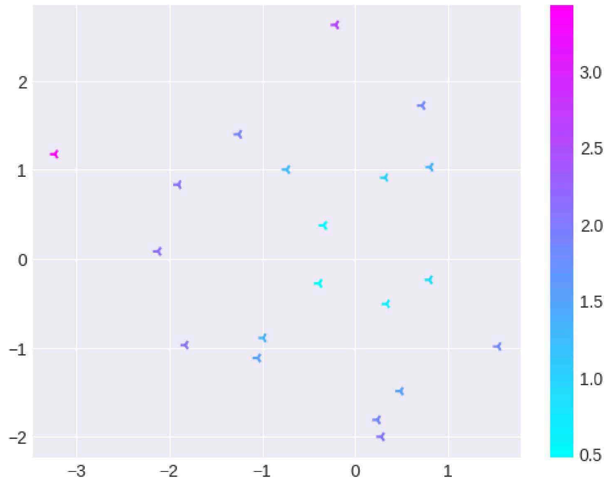


```
fig, axs = plt.subplots(2, 3, sharex=True, sharey=True, figsize=(16,12));
# plt.style.use('seaborn-darkgrid')
# marker symbol
axs[0, 0].scatter(x, y, s=80, marker=">")
axs[0, 0].set_title("marker='>'")

# marker from TeX
axs[0, 1].scatter(x, y, s=80, marker=r'$\alpha$')
axs[0, 1].set_title("marker = " + r'$\alpha$')
# axs[0, 1].set_title(f"marker = {r'$\alpha$'}")

# marker from path
verts = [[-1, -1], [1, -1], [1, 1], [-1, -1]]
axs[0, 2].scatter(x, y, s=80, marker=verts)
axs[0, 2].set_title("marker=verts")

axs[1, 0].scatter(x, y, s=80, marker=(5, 0))
axs[1, 0].set_title("marker=(5, 0)")

# regular star marker
axs[1, 1].scatter(x, y, s=80, marker=(5, 1))
axs[1, 1].set_title("marker=(5, 1)")

# regular asterisk marker
axs[1, 2].scatter(x, y, s=80, marker=(5, 2))
axs[1, 2].set_title("marker=(5, 2)");
```

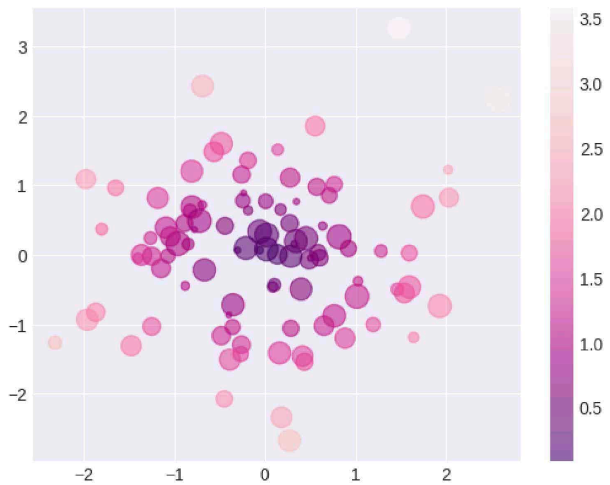


```
# setting the colors with matplotlib
plt.style.use('seaborn-darkgrid')

z1 = np.sqrt(x**2 + y**2)

fig, ax = plt.subplots()
pos = ax.scatter(x, y, c=z1, cmap='cool', marker='3')

fig.colorbar(pos);
```

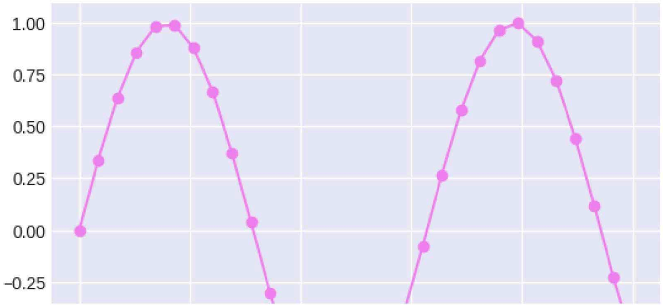
```
<ipython-input-51-3dd43bf91bb6>:2: MatplotlibDeprecationWarning: The seaborn styles shipped by Matplotlib are deprecated since 3.6,
  plt.style.use('seaborn-darkgrid')
```




```
x = np.random.randn(100)
y = np.random.randn(100)

z1 = np.sqrt(x**2 + y**2)
z2 = np.random.randint(10, 200, size=len(x))

fig, ax = plt.subplots()
# pos = ax.scatter(x, y, c=z1, s=z2, alpha = 0.55, cmap='viridis')
pos = ax.scatter(x, y, c = z1, s = z2, alpha = 0.55, cmap='RdPu_r')
fig.colorbar(pos);
```

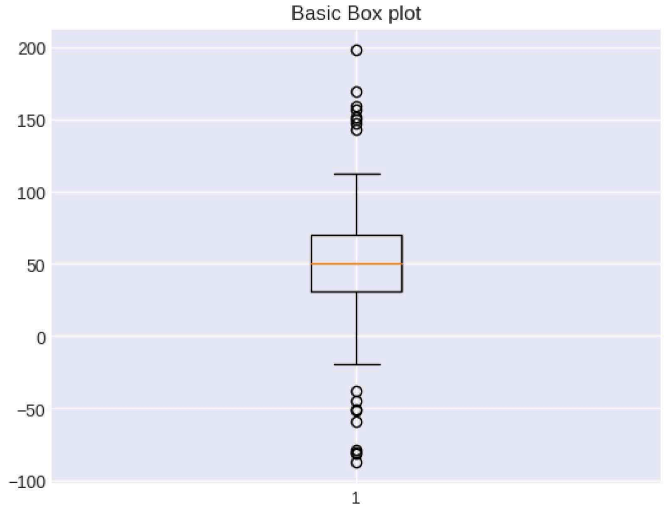



```
x = np.linspace(0, 10, 30)
y = np.sin(x)

plt.plot(x, y, 'o-', color='violet');
```




```
# Box plots

# Generating the data
spread = np.random.rand(50) * 100
center = np.ones(25) * 50
flier_high = np.random.rand(10) * 100 + 100
flier_low = np.random.rand(10) * -100
data = np.concatenate((spread, center, flier_high, flier_low))

# Visualization of the data using box plot (basic)
fig, ax = plt.subplots()
ax.boxplot(data)
ax.set_title("Basic Box plot")
```

```
Text(0.5, 1.0, 'Basic Box plot')
```




```
# Notched boxplot without outliers
```

LABSHEET 7

```
import pandas as pd
```

+ Code + Text

```
df = pd.read_csv('train.csv')
df
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Cabin	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	NaN	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C85	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	NaN	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	C123	S
4	5	0	3	Allen, Mr. William Henry	male	35.0	0	0	373450	8.0500	NaN	S
...	...	...	...	...	...	...	...	...	...	...	...	...
886	887	0	2	Montvila, Rev. Juozas	male	27.0	0	0	211536	13.0000	NaN	S
887	888	1	1	Graham, Miss. Margaret Edith	female	19.0	0	0	112053	30.0000	B42	S
888	889	0	3	Johnston, Miss. Catherine Helen "Carrie"	female	NaN	1	2	W./C. 6607	23.4500	NaN	S
889	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C148	C

```
df.dtypes
```

```
PassengerId      int64
Survived         int64
Pclass           int64
Name            object
Sex             object
Age            float64
SibSp            int64
Parch            int64
Ticket          object
Fare           float64
Cabin           object
Embarked        object
dtype: object
```

```
df.describe()
```

	PassengerId	Survived	Pclass	Age	SibSp	Parch	Fare
count	891.000000	891.000000	891.000000	714.000000	891.000000	891.000000	891.000000
mean	446.000000	0.383838	2.308642	29.699118	0.523008	0.381594	32.204208
std	257.353842	0.486592	0.836071	14.526497	1.102743	0.806057	49.693429
min	1.000000	0.000000	1.000000	0.420000	0.000000	0.000000	0.000000
25%	223.500000	0.000000	2.000000	20.125000	0.000000	0.000000	7.910400
50%	446.000000	0.000000	3.000000	28.000000	0.000000	0.000000	14.454200
75%	668.500000	1.000000	3.000000	38.000000	1.000000	0.000000	31.000000
max	891.000000	1.000000	3.000000	80.000000	8.000000	6.000000	512.329200

```
df.isna().sum()
```

```
PassengerId      0
Survived         0
Pclass           0
Name             0
Sex              0
Age            177
SibSp            0
Parch            0
Ticket           0
Fare             0
Cabin          687
Embarked         2
dtype: int64
```

```
age_mean_value=df['Age'].mean()
df['Age']=df['Age'].fillna(age_mean_value)
```

```
df.drop("Cabin",axis=1,inplace=True)
```

```
df.head()
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C
2	3	1	3	Heikkinen, Miss. Laina	female	26.0	0	0	STON/O2. 3101282	7.9250	S
3	4	1	1	Futrelle, Mrs. Jacques Heath (Lily May Peel)	female	35.0	1	0	113803	53.1000	S

```
filtered_age = df[df.Age>40]
filtered_age
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
6	7	0	1	McCarthy, Mr. Timothy J	male	54.0	0	0	17463	51.8625	S
11	12	1	1	Bonnell, Miss. Elizabeth	female	58.0	0	0	113783	26.5500	S
15	16	1	2	Hewlett, Mrs. (Mary D Kingcome)	female	55.0	0	0	248706	16.0000	S
33	34	0	2	Wheadon, Mr. Edward H	male	66.0	0	0	C.A. 24579	10.5000	S
35	36	0	1	Holverson, Mr. Alexander Oskar	male	42.0	1	0	113789	52.0000	S
...	...	...	...	...	...	...	...	...	...	...	...
862	863	1	1	Swift, Mrs. Frederick Joel (Margaret Welles Ba...	female	48.0	0	0	17466	25.9292	S
865	866	1	2	Bystrom, Mrs. (Karolina)	female	42.0	0	0	236852	13.0000	S
871	872	1	1	Beckwith, Mrs. Richard Leonard (Sallie Monypeny)	female	47.0	1	1	11751	52.5542	S
873	874	0	3	Vander Cruyssen, Mr. Victor	male	47.0	0	0	345765	9.0000	S
879	880	1	1	Potter, Mrs. Thomas Jr (Lily Alexenia Wilson)	female	56.0	0	1	11767	83.1583	C

```
# let's sort the column Name in ascending order
sorted_passengers = df.sort_values('Name',ascending=True,kind ='heapsort')
```

```
sorted_passengers.head(10)
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked
845	846	0	3	Abbing, Mr. Anthony	male	42.0	0	0	C.A. 5547	7.5500	S
746	747	0	3	Abbott, Mr. Rossmore Edward	male	16.0	1	1	C.A. 2673	20.2500	S
279	280	1	3	Abbott, Mrs. Stanton (Rosa Hunt)	female	35.0	1	1	C.A. 2673	20.2500	S
308	309	0	2	Abelson, Mr. Samuel	male	30.0	1	0	P/PP 3381	24.0000	C
874	875	1	2	Abelson, Mrs. Samuel (Hannah Wizosky)	female	28.0	1	0	P/PP 3381	24.0000	C
365	366	0	3	Adahl, Mr. Mauritz Nils Martin	male	30.0	0	0	C 7076	7.2500	S
401	402	0	3	Adams, Mr. John	male	26.0	0	0	341826	8.0500	S
40	41	0	3	Ahlin, Mrs. Johan (Johanna Persdotter Larsson)	female	40.0	1	0	7546	9.4750	S
855	856	1	3	Aks, Mrs. Sam (Leah Rosen)	female	18.0	0	1	392091	9.3500	S
207	208	1	3	Albimona, Mr. Nassef Cassem	male	26.0	0	0	2699	18.7875	C

```
merged_df = pd.merge(df.head(2),df.tail(2),how='outer',indicator=True)
merged_df
```

	PassengerId	Survived	Pclass	Name	Sex	Age	SibSp	Parch	Ticket	Fare	Embarked	_merge
0	1	0	3	Braund, Mr. Owen Harris	male	22.0	1	0	A/5 21171	7.2500	S	left_only
1	2	1	1	Cumings, Mrs. John Bradley (Florence Briggs Th...	female	38.0	1	0	PC 17599	71.2833	C	left_only
2	890	1	1	Behr, Mr. Karl Howell	male	26.0	0	0	111369	30.0000	C	right_only

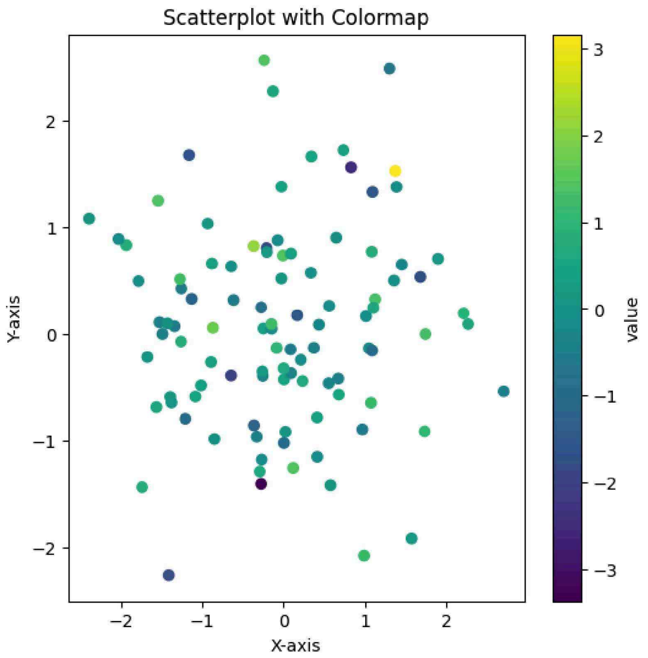
```
group_df = df.groupby('Name')
```

```
group_df
```

```
<pandas.core.groupby.generic.DataFrameGroupBy object at 0x111f7ad50>
```

LABSHEET 8

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
# Sample dataframe with multiple columns
data = pd.DataFrame({
    "x": np.random.randn(100),
    "y": np.random.randn(100),
    "value": np.random.randn(100)
})
# Define the colormap and alpha values
cmap = "viridis"
alpha = 1
# Create the scatterplot
plt.figure(figsize=(6, 6))
plt.scatter(data["x"], data["y"], c=data["value"], cmap=cmap, alpha=alpha)
# Customize the plot (optional)
plt.xlabel("X-axis")
plt.ylabel("Y-axis")
plt.title("Scatterplot with Colormap")
plt.colorbar(label="value")
# Show the plot
plt.show()
```




```
import pandas as pd
import numpy as np
print(np.random.randn(100))
```

```
[ 7.25060198e-01  2.53900412e+00  1.26528031e+00  1.84136990e+00
 -2.60848832e+00 -5.59983281e-01  4.35035456e-01 -7.00367135e-02
  1.96931749e+00  1.04382097e+00 -5.23481680e-01  4.38611173e-01
 -6.03314609e-02 -1.62331938e+00 -1.75368806e-01 -1.45327854e-01
  7.11162067e-01 -1.24752326e+00  1.10879435e+00  6.15797150e-01
  3.22382085e-02 -4.94204444e-01 -1.56553377e+00  1.86476127e+00
 -1.53372917e+00  6.21845005e-01  1.08857491e+00 -1.69076421e+00
 -3.80722950e+00  4.70410313e-01  8.77562643e-01 -8.95285501e-01
  9.83561836e-01  9.32718991e-01 -6.78531171e-01  9.14953408e-05
 -2.21344622e+00 -6.15124358e-02 -9.18144802e-02  7.84013469e-01
  9.64181023e-01 -1.75737978e+00  1.19471319e+00 -1.02246958e-01
  7.73172607e-01  1.02398382e+00  1.47867589e-01 -2.44199793e+00
 -8.49499655e-01  1.88210306e-01 -2.61106287e-01 -9.53558247e-01
 -8.54821744e-01 -3.80648950e-01 -5.87306646e-01  5.54602769e-01
  1.40580004e+00  1.08580790e+00 -8.33862936e-01  7.08280769e-01
 -1.43281505e+00 -1.93642975e-01  6.86796860e-01  5.50748349e-01
  7.79495185e-01 -2.71795003e-01 -1.16407843e+00  1.38373041e+00
 -2.90569948e-01  1.27385062e+00 -4.24752220e-01  5.69263764e-01
 -1.45006382e+00  8.39335515e-01 -9.49539071e-01 -2.04611107e+00
  1.00680640e+00  2.59974257e-01 -1.29858485e+00  9.67979863e-01
 -9.72496062e-01 -1.72551385e+00 -5.42038103e-01  4.26256470e-01
```

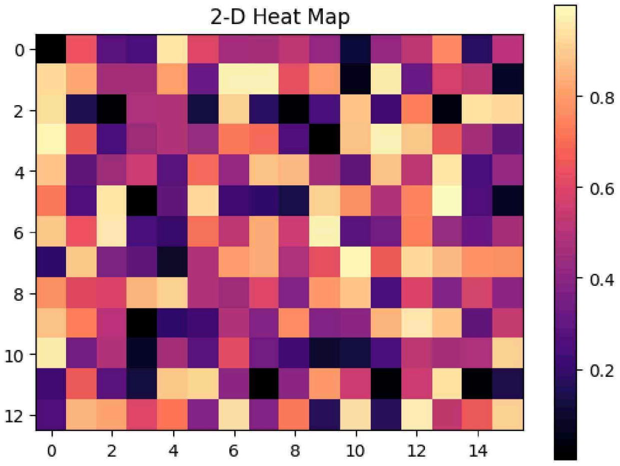
```
 6.57253328e-01 -1.75193447e+00 -1.22202143e+00 -6.31901884e-01
-9.24312354e-01  1.76235295e+00 -6.83714121e-01  5.19175365e-01
-3.18749238e-01 -1.69096151e-01 -4.49121798e-01  3.98598713e-01
 8.80300195e-01 -6.39043290e-02 -4.47122464e-01 -1.65126924e-01]
```

Start coding or generate with AI.

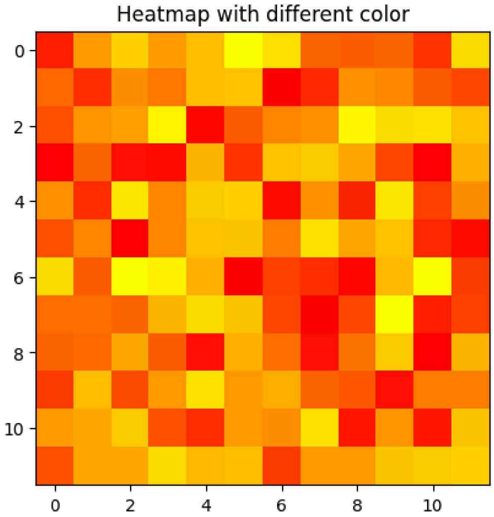
Double-click (or enter) to edit

LABSHEET 9

```
# Program to plot 2-D Heat map
# using matplotlib.pyplot.imshow() method
import numpy as np
import matplotlib.pyplot as plt
data = np.random.random(( 13 , 16 ))
plt.imshow( data,cmap="magma" )
plt.title( "2-D Heat Map" )
plt.colorbar()
plt.show()
```

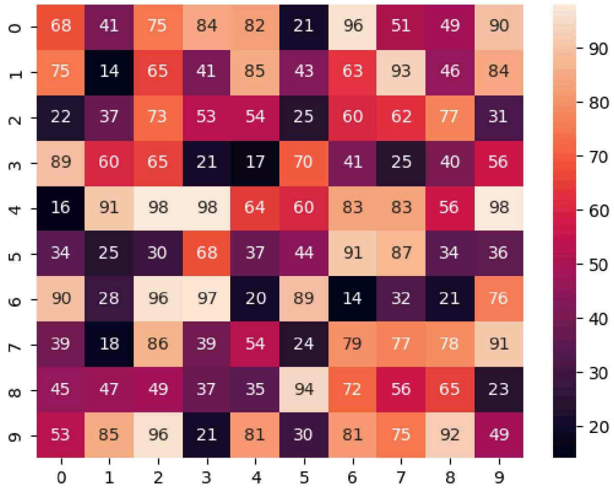



```
# Program to plot 2-D Heat map
# using matplotlib.pyplot.imshow() method
import numpy as np
import matplotlib.pyplot as plt

data = np.random.random((12, 12))
plt.imshow(data, cmap='autumn')

plt.title("Heatmap with different color")
plt.show()
```




```
# importing the modules
import numpy as np
import seaborn as sns
import matplotlib.pyplot as plt

# generating 2-D 10x10 matrix of random numbers
# from 1 to 100
data = np.random.randint(low=14,
                         high=100,
```

```
                        size=(10, 10))
# plotting the heatmap
hm = sns.heatmap(data=data,annot=True)
# displaying the plotted heatmap
plt.show()
```



*All the IPython Notebooks in **Python Seaborn Module** lecture series by **Dr. Milaan Parmar** are available @ **GitHub***

LABSHEET 10

Open in Colab

Seaborn Color Palettes

Color is an utmost important aspect of figure styling because it reveals pattern in the data if used effectively; or hide those patterns if used poorly. Even professionals often assume usage of color to portray data as a solved problem. They just pick a palette from a drop-down menu (probably either a grayscale ramp or a rainbow), set start and end points & finally press apply. But it isn't that simple and thus many visualizations fail to represent the underlying data as appropriately as they could.

Primary objective with choice of color is to illuminate datapoints that are concealed in huge datasets. Quoting Robert Simmon:

> Although the basics are straightforward, a number of issue complicate color choices in visualization. Among them: The relationship between the light we see and the colors we perceive is extremely complicated. There are multiple types of data, each suited to a different color scheme. A significant number of people (mostly men), are color blind. Arbitrary color choices can be confusing for viewers unfamiliar with a data set. Light colors on a dark field are perceived differently than dark colors on a bright field, which can complicate some visualization tasks, such as target detection.

One of the most fundamental and important aspects of color selection is the mapping of numbers to colors. This mapping allows us to pseudocolor an image or object based on varying numerical data. By far, the most common color map used in scientific visualization is the *rainbow* color map. Research paper on **Diverging Color Maps for Scientific Visualization** by Kenneth Moreland very well deals with the extended color concepts, if the topic interests you for further analysis.

With all that been said, let us now focus on what Seaborn has to offer BUT before doing that let me once again remind you that Seaborn runs on top of Matplotlib so any color that is supported by **Matplotlib** will be supported by Seaborn as well. So at first, let us understand what Matplotlib has to offer:

- an RGB or RGBA tuple of float values in [0, 1] (e.g., (0.1, 0.2, 0.5) or (0.1, 0.2, 0.5, 0.3))
- a hex RGB or RGBA string (e.g., '#0F0F0F' or '#0F0F0F0F')
- a string representation of a float value in [0, 1] inclusive for gray level (e.g., '0.5')
- one of {'b', 'g', 'r', 'c', 'm', 'y', 'k', 'w'}
- a X11/CSS4 color name
- a name from the xkcd color survey prefixed with 'xkcd:' (e.g., 'xkcd:sky blue')
- one of {'C0', 'C1', 'C2', 'C3', 'C4', 'C5', 'C6', 'C7', 'C8', 'C9'}
- one of {'tab:blue', 'tab:orange', 'tab:green', 'tab:red', 'tab:purple', 'tab:brown', 'tab:pink', 'tab:gray', 'tab:olive', 'tab:cyan'} which are the **Tableau** Colors from the 'T10' categorical palette (which is the default color cycle).

Note that all string specifications of color, other than "CN", are NOT case-sensitive. Let us briefly go through a couple of common supported colors here:

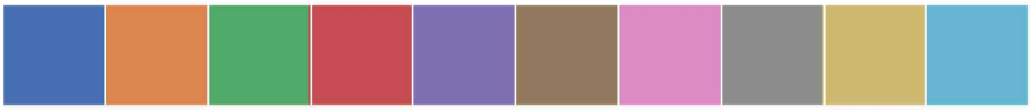
- RGB/RGBA tuples are 4-tuples where the respective tuple components represent Red, Green, Blue, and Alpha (opacity) values for a color. Each value is a floating point number between 0.0 and 1.0. For example, the tuple (1, 0, 0, 1) represents an opaque red, while (0, 1, 0, 0.5) represents a half transparent green.
- This is actually another way of representing RGBA codes and common Color Conversion Calculators can be used to translate values. Here is a **Hex to RGBA** and **RGB to Hex** Color converter for your future assistance.
- Dictionary of values from {'C0', 'C1', 'C2', 'C3', 'C4', 'C5', 'C6', 'C7', 'C8', 'C9'} represent **Color Quantization**. I have attached a link in the provided notebook that shall guide you to an online book where on Page-29 you could find specifics.

My sole purpose of keeping you posted of Matplotlib background every now and then is only to ensure that when you get to production-level and try to customize a plot as per your analysis, you should know what is ACTUALLY running in the background. This shall empower you to accordingly tweak parameters here and there. Let us now look into few Seaborn options for colors:

```
# Importing required Libraries:
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline

# Setting a figure size for all the plots we shall be drawing in this kernel:
sns.set(rc={"figure.figsize": (6, 6)})
```

Building color palettes:

```
current_palette = sns.color_palette()
sns.palplot(current_palette)
```

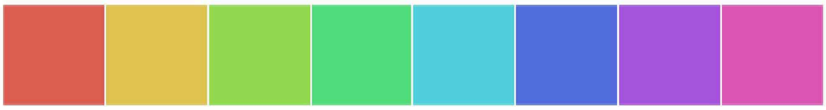


The most important function for working with discrete color palettes is `color_palette()`. This function provides an interface to many (though not all) of the possible ways you can generate colors in seaborn, and it's used internally by any function that has a `palette` argument (and in some cases for a `color` argument when multiple colors are needed).

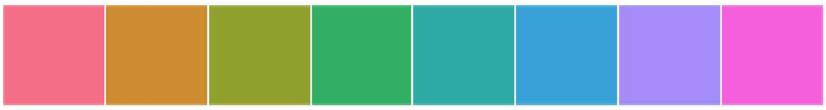
`color_palette()` will accept the name of any seaborn palette or matplotlib colormap (except `jet`, which you should never use). It can also take a list of colors specified in any valid matplotlib format (RGB tuples, hex color codes, or HTML color names). The return value is always a list of RGB tuples.

Finally, calling `color_palette()` with no arguments will return the current default color cycle.

```
sns.palplot(sns.color_palette("hls", 8))
```



```
sns.palplot(sns.color_palette("husl", 8))
```

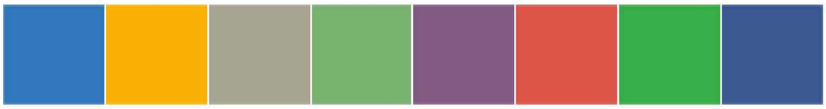


Let me explain these Qualitative (or categorical) palettes. These are best when you want to distinguish discrete chunks of data that do not have an inherent ordering. Ideally, when importing Seaborn, the default color cycle is changed to a set of six colors that evoke the standard matplotlib color cycle. But when we have more than 6, say 8 categories in our data to distinguish, then the most common way is using `hls` color space, which is a simple transformation of *RGB* values.

Then there is also `hls_palette()` function that lets you control the *lightness* and *saturation* of colors.

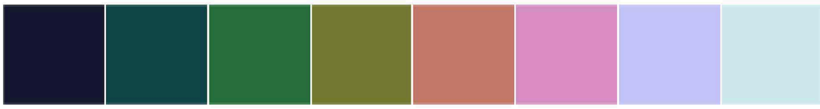
All of it displayed above is just the basic Seaborn aesthetics. Let us now look at *xkcd_rgb* dictionary that has 954 colors in it. Let us try to pull a few out of it:

```
sample_colors = ["windows blue", "amber", "greyish", "faded green", "dusty purple", "pale red",
sns.palplot(sns.xkcd_palette(sample_colors))
```

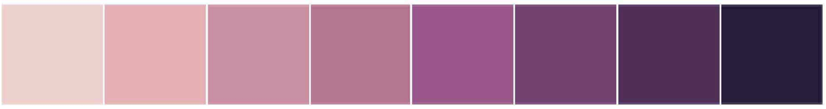


Other style is **`cubehelix`** color palette that makes sequential palettes with a linear increase or decrease in brightness and some variation in **[hue](#)**. Actually let us plot this color palette in a Density contour plot:

```
# Default Matplotlib Cubehelix version:
sns.palplot(sns.color_palette("cubehelix", 8))
```

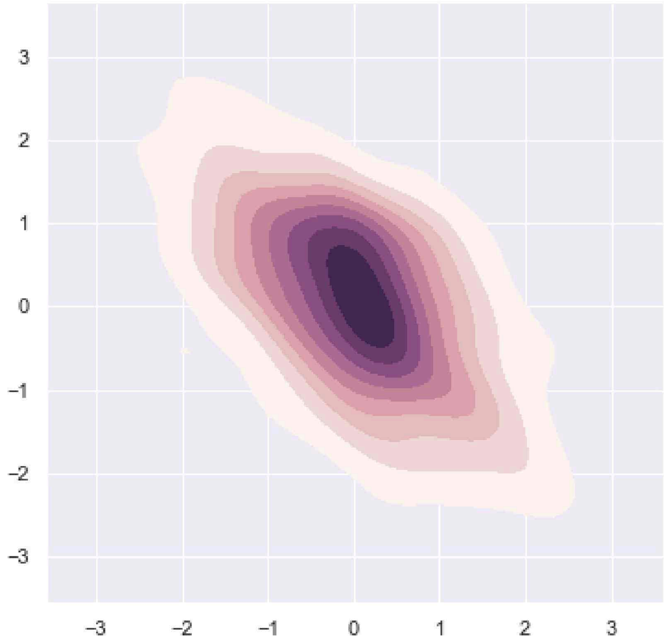


```
# Default Seaborn Cubehelix version:
sns.palplot(sns.cubehelix_palette(8))
```



```
# Density Plot with Seaborn defaults:
x, y = np.random.multivariate_normal([0, 0], [[1, -.5], [-.5, 1]], size=300).T

sample_cmap = sns.cubehelix_palette(light=1, as_cmap=True)
sns.kdeplot(x, y, cmap=sample_cmap, shade=True)
```

```
C:\ProgramData\Anaconda3\lib\site-packages\seaborn\_decorators.py:36: FutureWarning:
  warnings.warn(
<AxesSubplot:>
```



Interactive widget to create a sequential cubehelix palette:

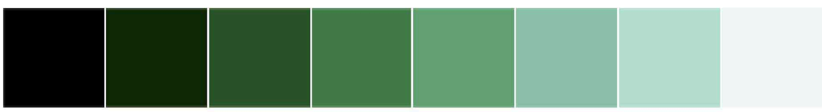
Let us now play with the parameters to have some fun and choose best parameters:

```
sns.choose_cubehelix_palette(as_cmap=True)
```

```
---------------------------------------------------------------------------
NameError                                 Traceback (most recent call last)
<ipython-input-1-230a1c9055e9> in <cell line: 1>()
----> 1 sns.choose_cubehelix_palette(as_cmap=True)

NameError: name 'sns' is not defined
```

Note that this app only works in this Jupyter Notebook as of now to help choose best parameters for our plot:

```
sns.palplot(sns.cubehelix_palette(n_colors=8, start=1.7, rot=0.2, dark=0, light=.95, reverse=Tru
```

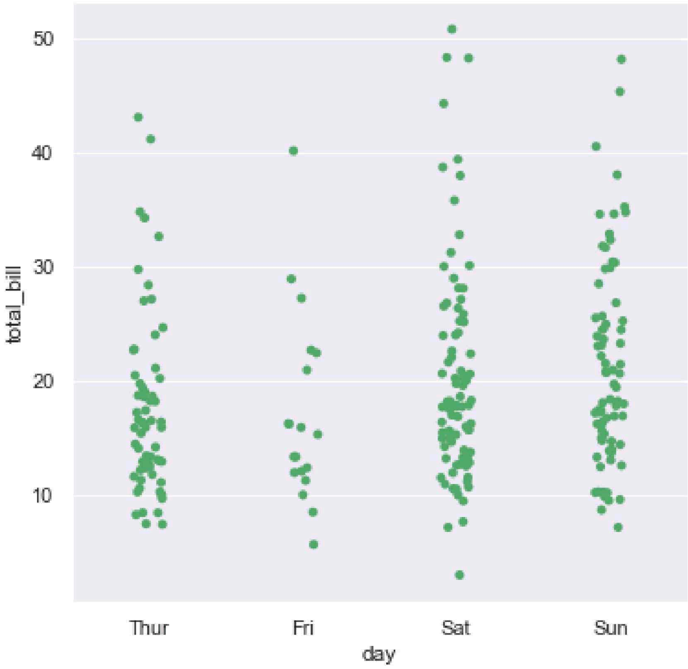


start is always between 0 and 3. *rot* an abbreviation for rotation is kept between -1 and 1. *reverse* converses the color ordering and *hue* refers to plot appearance.

Generic Seaborn Plots:

```
# Loading up built-in dataset:
tips = sns.load_dataset("tips")

# Creating Strip plot for day-wise revenue:
sns.stripplot(x="day", y="total_bill", data=tips, color="g")
```

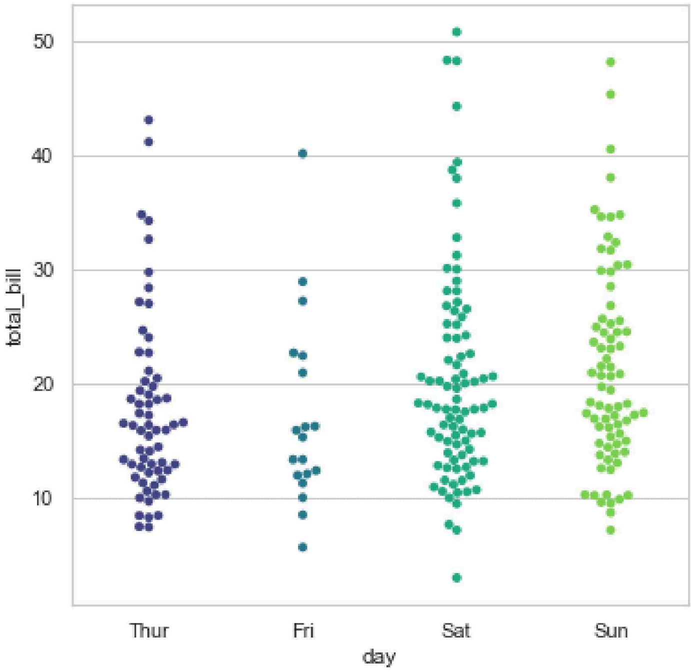
```
<AxesSubplot:xlabel='day', ylabel='total_bill'>
```



This does the job for us but let us try to get better results by plotting each day in different color instead of same color. For this, we shall replace `color` parameter with `palette` parameter:

```
# Set Theme:
sns.set_style('whitegrid')

# Creating Strip plot for day-wise revenue:
sns.swarmplot(x="day", y="total_bill", data=tips, palette="viridis")
```

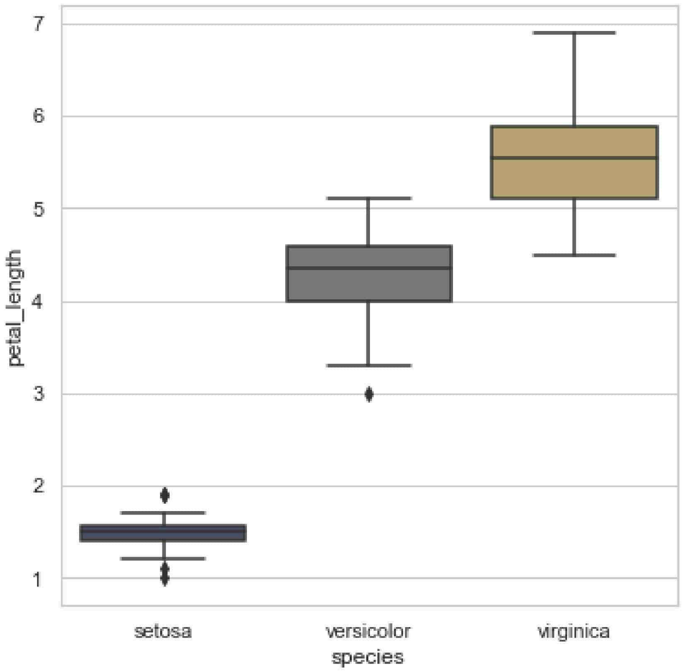
```
<AxesSubplot:xlabel='day', ylabel='total_bill'>
```



Similarly, let us plot one more and for a change, this time we shall plot a Violin plot:

```
iris = sns.load_dataset("iris")

sns.boxplot(x="species", y="petal_length", data=iris, palette="cividis")
```

```
<AxesSubplot:xlabel='species', ylabel='petal_length'>
```



There are multiple such palette available for us to play around with like magma, warm grey, gunmetal, dusky blue, cool blue, deep teal, viridian, twilight blue and many more. For customized color brewing, we may also use *color brewer* that also offers interesting color palettes for working with Qualitative data. The cool thing about it is that you can use the an interactive Ipython widget function to make the selection of the palette. For this, you only need to use `choose_colorbrewer_palette()`.

There are multiple such palette available for us to play around with like magma, warm grey, gunmetal, dusky blue, cool blue, deep teal, viridian, twilight blue and many more. For customized color brewing, we may also use *color brewer* that also offers interesting color palettes for working with Qualitative data. A nice feature of the **Color Brewer website** is that it provides some guidance on which palettes are color blind safe.

The cool thing about it is that you can use the an interactive Ipython widget function to make the selection of the palette. For this, you only need to use `choose_colorbrewer_palette()`. To access this on your web browser, please access **ColorBrewer** link provided in the notebook.

I also found a nice representation of Color Schemes in Seaborn, that I found somewhere on web, so thought of sharing it in your Resource bucket to check out if you wish to. Let's have a look at it

LABSHEET 11

```
#Installation
#pip install seaborn
```

Seaborn2

Figure

Figure

It refers to the whole figure that you see. It is possible to have multiple sub-plots (Axes) in the same figure.

Axes

An Axes refers to the actual plot in the figure. A figure can have multiple Axes but a given Axes can be part of only one figure.

Axis

An Axis refers to an actual axis (x-axis/y-axis) in a specific plot.

Four sub-plots (Axes) in a single figure.

Figure2

Seaborn

Seaborn - can create complicated plot types from Pandas data with relatively simple commands

Plotting in seaborn is either : Axes-level functions OR Figure-level function

PLOT CATEGORIES IN SEABORN

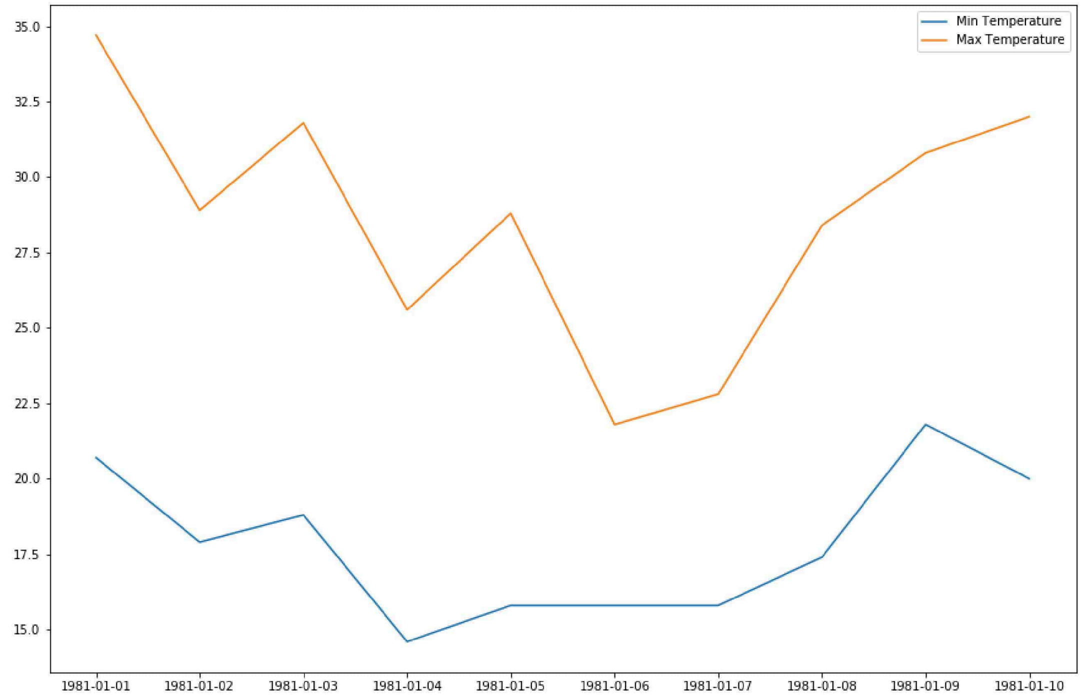
I. Relational plots : This plot is used to understand the relation between two variables.
II. Categorical plots: This plot deals with categorical variables and how they can be visualized.
III. Distribution plots: This plot is used for examining univariate and bivariate distributions
IV. Matrix plots: A matrix plot is an array of scatterplots.
V. Regression plots: The regression plots in seaborn are primarily intended to add a visual guide that helps to emphasize patterns in a dataset during exploratory data analyses.

Seaborn

```
#Import necessary Packages
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
from matplotlib.pyplot import figure

import seaborn as sns

%matplotlib inline
```

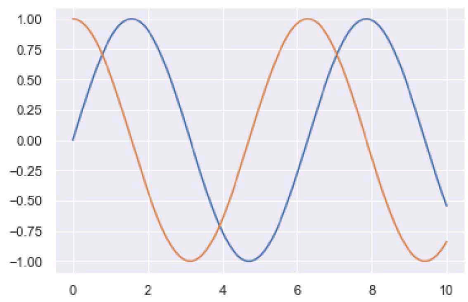
```
#Simple Plotting with Seaborn

#Data
dates = ['1981-01-01', '1981-01-02', '1981-01-03', '1981-01-04', '1981-01-05',
        '1981-01-06', '1981-01-07', '1981-01-08', '1981-01-09', '1981-01-10' ]

min_temperature = [20.7, 17.9, 18.8, 14.6, 15.8, 15.8, 15.8, 17.4, 21.8, 20.0]
max_temperature = [34.7, 28.9, 31.8, 25.6, 28.8, 21.8, 22.8, 28.4, 30.8, 32.0]

#Plotting
fig,axes = plt.subplots(nrows=1, ncols=1, figsize=(15,10))
axes.plot(dates, min_temperature, label='Min Temperature')
axes.plot(dates, max_temperature, label = 'Max Temperature')
axes.legend()
```

```
<matplotlib.legend.Legend at 0x1c0d2b24748>
```



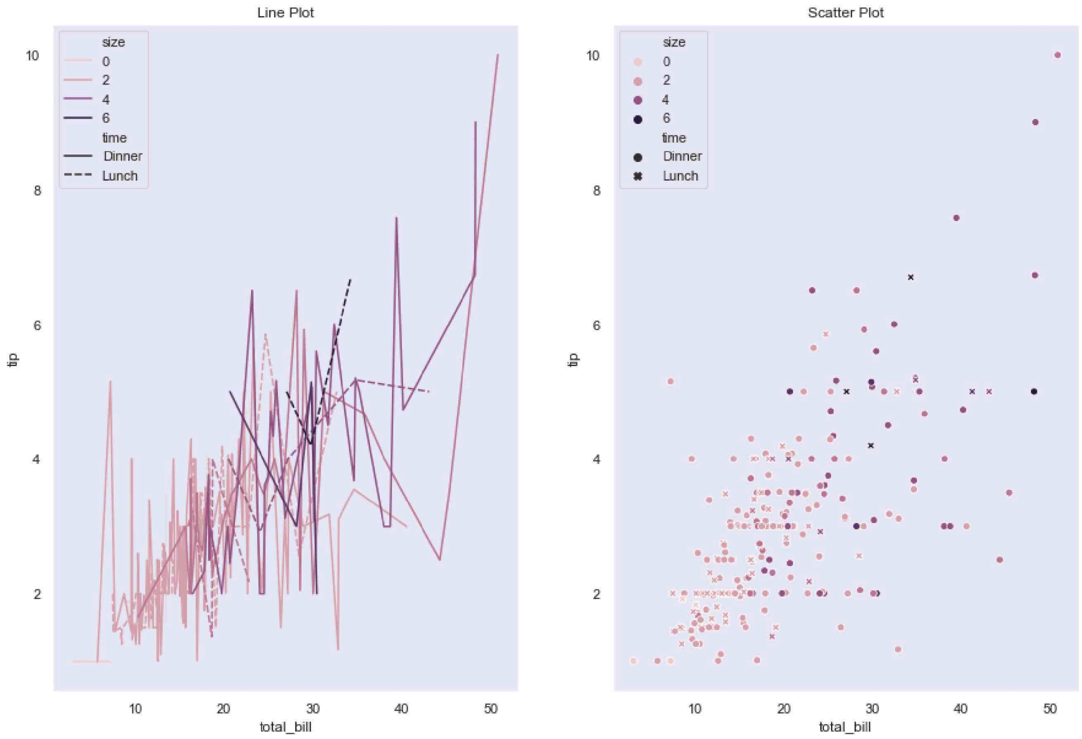

```
#seaborn style as the default matplotlib style
sns.set()
```

```
#Simple sine plot
x = np.linspace(0, 10, 1000)
plt.plot(x, np.sin(x), x, np.cos(x));
```



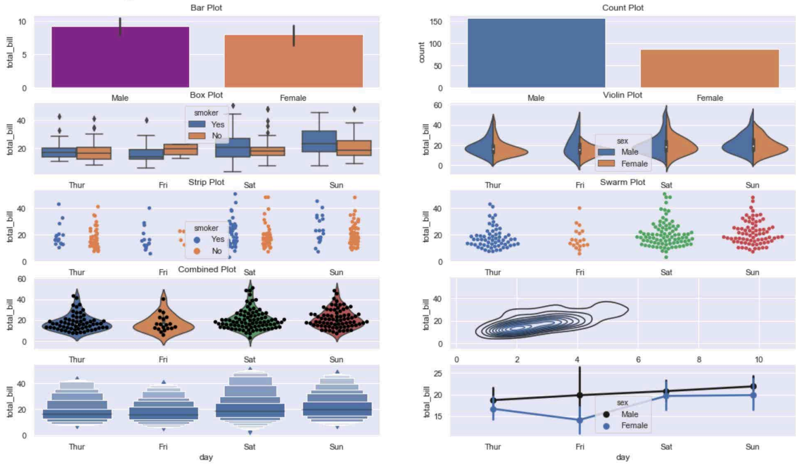
```
# I. Relational Plots

# Line plot : The line plot is one of the most basic plot in seaborn library.
#This plot is mainly used to visualize the data in form of some time series, i.e. in continuous manner.
sns.set(style="dark")
fig, ax = plt.subplots(ncols=2, nrows=1, figsize=(15,10))

#Loading Data with Seaborn
df = sns.load_dataset("tips")

print(df.head())

#lineplot
sns.lineplot(x="total_bill", y="tip", hue="size", style="time", data=df,ax=ax[0]).set_title("Line Plot")


#scatterplot
Sct_plt=sns.scatterplot(x="total_bill", y="tip", hue="size", style="time", data=df,ax=ax[1]).set_title("Scatter Plot")

#Saving Plot
Sct_plt.figure.savefig('Scatter_plot1.png')
print('Plot Saved')
```

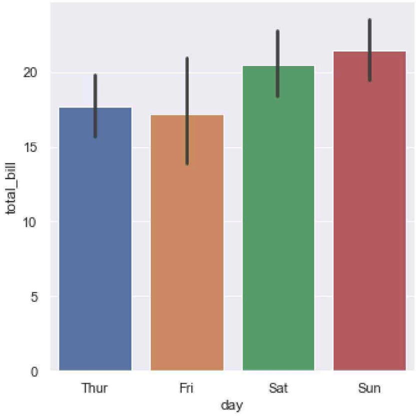
```
   total_bill   tip     sex smoker  day    time  size
0       16.99  1.01  Female     No  Sun  Dinner     2
1       10.34  1.66    Male     No  Sun  Dinner     3
2       21.01  3.50    Male     No  Sun  Dinner     3
3       23.68  3.31    Male     No  Sun  Dinner     2
4       24.59  3.61  Female     No  Sun  Dinner     4
Plot Saved
```



```
#II. Categorical Plots
#Plots are basically used for visualizing the relationship between variables.
#Variables can be either be completely numerical or a category like a group, class or division.

sns.set_style('darkgrid')
fig, ax =plt.subplots(nrows=5,ncols=2)
fig.set_size_inches(18.5, 10.5)

#Data
# 'tips' dataset contains information about people who probably had food at a restaurant
#  whether or not they left a tip for the waiters, their gender, whether they smoke and so on.
df = sns.load_dataset('tips')

#barplot -  basically used to aggregate the categorical data according to some methods and by default its the mean
sns.barplot(x ='sex', y ='total_bill', data = df,palette ='plasma', estimator = np.std,ax=ax[0,0]).set_title('Bar Plot')


#countplot -Counts the categories and returns a count of their occurrences
sns.countplot(x ='sex', data = df,ax=ax[0,1]).set_title('Count Plot')

#boxplot - known as the box and whisker plot.
#It shows the distribution of the quantitative data that represents the comparisons between variables
sns.boxplot(x ='day', y ='total_bill', data = df, hue ='smoker',ax=ax[1,0]).set_title('Box Plot')

# Similar to the boxplot except that it provides a higher, more advanced visualization
# Uses the kernel density estimation to give a better description about the data distribution.
sns.violinplot(x ='day', y ='total_bill', data = df, hue ='sex', split = True,ax=ax[1,1]).set_title('Violin Plot')

#Stripplot -  scatter plot based on the category
sns.stripplot(x ='day', y ='total_bill', data = df, jitter = True, hue ='smoker', dodge = True,ax=ax[2,0]).set_title('Strip Plot')

#Swarmplot-similar to stripplot except the fact that the points are adjusted so that they do not overlap.
sns.swarmplot(x ='day', y ='total_bill', data = df,ax=ax[2,1]).set_title('Swarm Plot')

#Combining the idea of a violin plot and a stripplot to form this plot
sns.violinplot(x ='day', y ='total_bill', data = df,ax=ax[3,0])
sns.swarmplot(x ='day', y ='total_bill', data = df, color ='black',ax=ax[3,0]).set_title('Combined Plot')

# Density Plot
sns.kdeplot(df['tip'], df['total_bill'],ax=ax[3,1])

#boxenplot
sns.boxenplot(x="day", y="total_bill",color="b", scale="linear", data=df,ax=ax[4,0])

#Ridgeplot
sns.pointplot(x="day", y="total_bill",color="b", hue="sex", data=df,ax=ax[4,1])

#catplot
#General plot -  provides a parameter called 'kind' to choose the kind of plot ,better that writing the plots separately.
#The kind parameter can be bar, violin, swarm etc.
sns.catplot(x ='day', y ='total_bill', data = df, kind ='bar')
```

```
<seaborn.axisgrid.FacetGrid at 0x1c0d3615888>
```



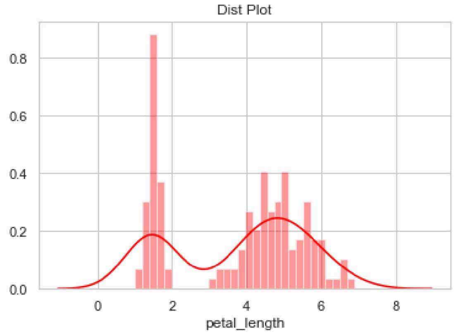


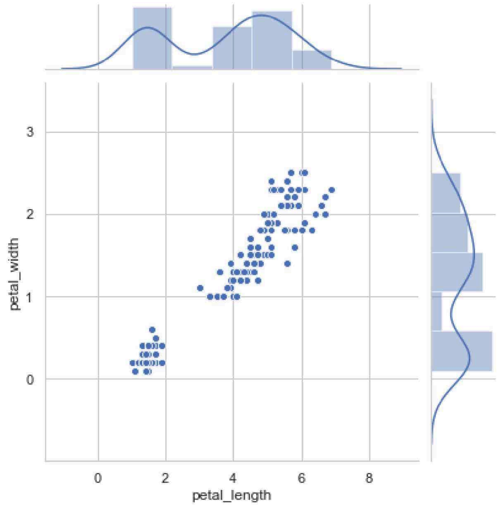
III. **Distribution plots** in seaborn is used for examining univariate and bivariate distributions. 4 main types of distribution plots :

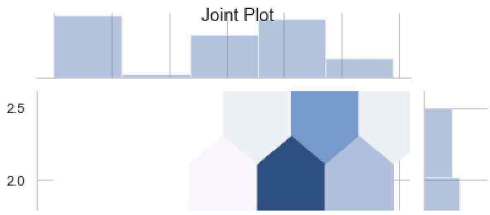
```
joinplot
distplot
pairplot
rugplot
```

```
sns.set_style('whitegrid')


#Data - 'iris'
df = sns.load_dataset('iris')
print(df.head())

#Displot- used for univariant set of observations and visualizes it through a histogram
#i.e. only one observation and hence we choose one particular column of the dataset.
#KDE is a way to estimate the probability density function (PDF) of the random variable that “underlies” the sample.
#KDE is a means of data smoothing.
#bins is used to set the number of bins you want in your plot and it actually depends on your dataset.
#color is used to specify the color of the plot
sns.distplot(df['petal_length'], kde = True, color ='red', bins = 30).set_title('Dist Plot')

#Joinplot/jointgrid- draw a plot of two variables with bivariate and univariate graphs. It basically combines two different plots.
#Plot a bi-variate distribution along with marginal distributions in the same plot
#Joint Distribution of two variables can be visualised using scatter plot/regplot or kdeplot.
#Marginal Distribution of variables can be visualised by histograms and/or kde plot
#KDE shows the density where the points match up the most
#The Axes-level function to use for joint distribution must be passed to JointGrid.plot_joint().
#The Axes-level function to use for marginal distribution must be passed to JointGrid.plot_marginals()

jointgrid = sns.JointGrid(x='petal_length', y='petal_width', data=df)
jointgrid.plot_joint(sns.scatterplot)
jointgrid.plot_marginals(sns.distplot)

#jointplot() to plot bi-variate distribution along with marginal distributions.
#It uses JointGrid() and JointGrid.plot_joint() in the background.
g=sns.jointplot(x = 'petal_length',y = 'petal_width',data = df,kind = 'hex')
g.fig.suptitle('Joint Plot')

#Pairplot-  pairwise relation across the entire dataframe
#hue sets up the categorical separation between the entries in the dataset.
#palette is used for designing the plots.
g=sns.pairplot(df, hue ="species", palette ='coolwarm')
g.fig.suptitle("Pair Plot 1")
g.add_legend()


#PairGrid() - creates Axes for each pair of variables
#PairGrid.map() - draws the plot on each Axes using data corresponding to that pair of variables
pairgrid = sns.PairGrid(data=df)
pairgrid = pairgrid.map_offdiag(sns.scatterplot)
pairgrid = pairgrid.map_diag(plt.hist)

#Different kind of plots on Upper Triangular Axes, Diagonal Axes and Lower Triangular Axes.
pairgrid = sns.PairGrid(data=df)
pairgrid = pairgrid.map_upper(sns.scatterplot)
pairgrid = pairgrid.map_diag(plt.hist)
pairgrid = pairgrid.map_lower(sns.kdeplot)

#Avoid Redundancy
g = sns.PairGrid(df, diag_sharey=False, corner=True)
g.map_lower(sns.scatterplot)
g.map_diag(sns.kdeplot)
```

```
   sepal_length  sepal_width  petal_length  petal_width species
0           5.1          3.5           1.4          0.2  setosa
1           4.9          3.0           1.4          0.2  setosa
2           4.7          3.2           1.3          0.2  setosa
3           4.6          3.1           1.5          0.2  setosa
4           5.0          3.6           1.4          0.2  setosa
<seaborn.axisgrid.PairGrid at 0x1c0d2b15888>
```







LABSHEET 12

Load the Pacakges

To get started, open a Colab notebook and load the Pandas, Matplotlib, and Wordcloud packages.

```
import pandas as pd
import matplotlib.pyplot as plt
from wordcloud import WordCloud
from wordcloud import STOPWORDS
```

Mount the drive and read the CSV file from the drive.

Here we are going to use netflix_titles.csv dataset downloaded from kaggle.

Since it is text visualization we are going to consider only one column.

```
from google.colab import drive
```

```
drive.mount('/content/drive/')
```

```
Mounted at /content/drive/
```

```
df=pd.read_csv('/content/drive/My Drive/Data/netflix_titles.csv', usecols=['cast'])
df.head()
```

	cast
0	NaN
1	Ama Qamata, Khosi Ngema, Gail Mabalane, Thaban...
2	Sami Bouajila, Tracy Gotoas, Samuel Jouy, Nabi...
3	NaN
4	Mayur More, Jitendra Kumar, Ranjan Raj, Alam K...

Perform Prepeocessing to remove the records containing NaN

```
ndf=df.dropna()
ndf.head()
```

	cast
1	Ama Qamata, Khosi Ngema, Gail Mabalane, Thaban...
2	Sami Bouajila, Tracy Gotoas, Samuel Jouy, Nabi...
4	Mayur More, Jitendra Kumar, Ranjan Raj, Alam K...
5	Kate Siegel, Zach Gilford, Hamish Linklater, H...
6	Vanessa Hudgens, Kimiko Glenn, James Marsden, ...

The wordcloud package requires single string instead of column.

Joining the all text data of the coloumn 'cast' to single string to make text visualization easy

```
text = " ".join(item for item in ndf['cast'])
print(text)
```

```
Ama Qamata, Khosi Ngema, Gail Mabalane, Thabang Molaba, Dillon Windvogel, Natasha Thahane, Arno Greeff, Xolile Tshabalala, Getmore S
```

Sometimes, there will be words in your dataframe that are insignificant and don't add any insight. We can take these out using the STOPWORDS module which is included in Wordcloud.

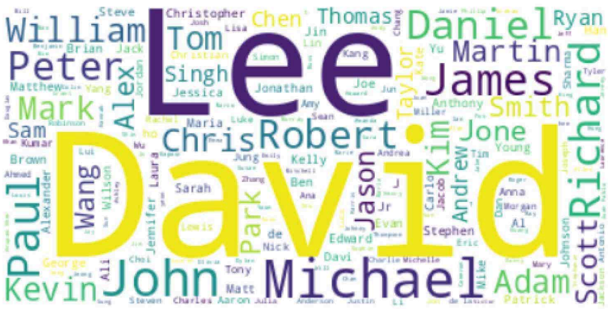
```
stopwords = set(STOPWORDS)
```

Create a basic word cloud

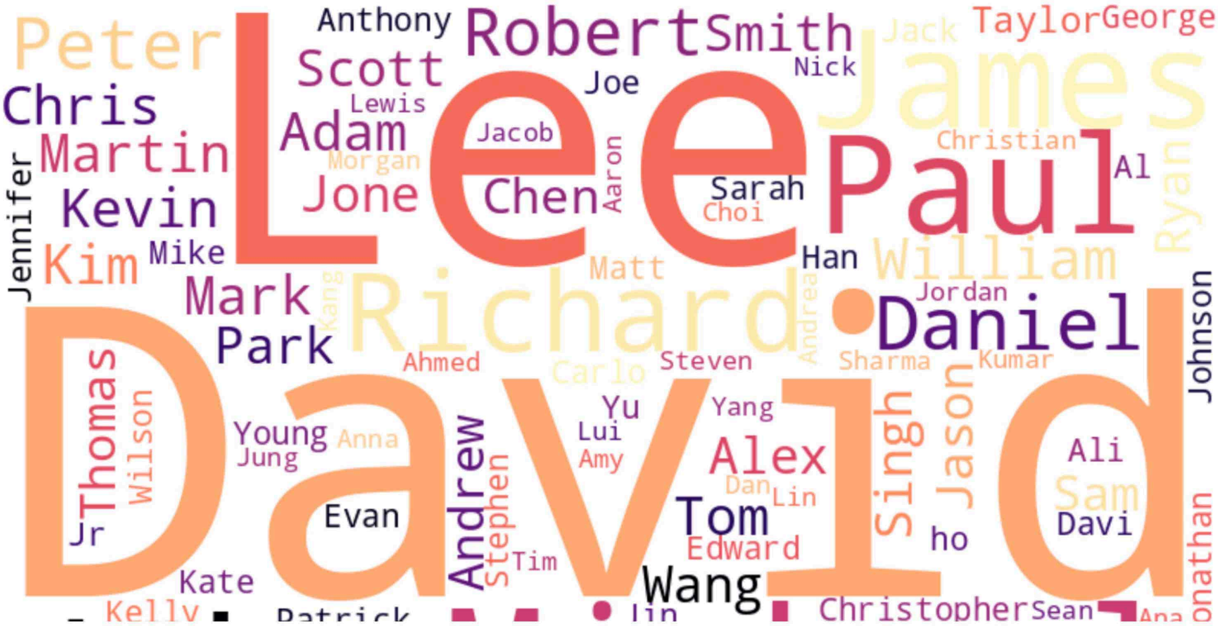
By instantiating WordCloud and then appending generate(text), we can pass in our big list of words and WordCloud will calculate the word frequencies, and determine the sizes, and colours of each of the words shown based on their frequencies within the text.

The other bits of Matplotlib code turn off the axes and ticks to make the word cloud look a bit neater.

```
wordcloud = WordCloud(background_color="white").generate(text)
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.margins(x=0, y=0)
plt.show()
```




```
wordcloud = WordCloud(background_color="white",
                      max_words=100,
                      max_font_size=300,
                      width=800,
                      height=500,
                      colormap="magma"
                     ).generate(text)

plt.figure(figsize=(20,20))
plt.imshow(wordcloud, interpolation='bilinear')
plt.axis("off")
plt.margins(x=0, y=0)
plt.savefig("cloud.jpg", format="jpg")
plt.show()
```


Peter
Lee
Anthony
Robert
Smith
Jack
Taylor
George
James
Scott
Nick
Chris
Lewis
Joe
Adam
Jacob
Martin
Morgan
Christian
Paul
Al
Jennifer
Jone
Chen
Aaron
Sarah
Ryan
Kevin
Choi
Kim
Mike
Matt
Han
William
Mark
Kang
Richard
Andrea
Jordan
Daniel
Park
Ahmed
Carlo
Steven
Sharma
Kumar
Johnson
David
Thomas
Wilson
Yu
Yang
Singh
Jason
Young
Anna
Lui
Alex
Ali
Jung
Amy
Andrew
Stephen
Dan
Lin
Sam
Evan
Tom
Jr
Davi
ho
Edward
Tim
Kate
Wang
Christopher
Sean
Kelly
Patrick

LABSHEET 13

A time series is the series of data points listed in time order.

A time series is a sequence of successive equal interval points in time.

A time-series analysis consists of methods for analyzing time series data in order to extract meaningful insights and other useful characteristics of data.

For performing time series analysis download stock_data.csv

```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
```

```
# reading the dataset using read_csv
df = pd.read_csv(r"stock_data.csv")
# displaying the first five rows of dataset
df.head()
```

	Date	Open	High	Low	Close	Volume	Name
0	1/3/2006	39.69	41.22	38.79	40.91	24232729	AABA
1	1/4/2006	41.22	41.90	40.77	40.97	20553479	AABA
2	1/5/2006	40.93	41.73	40.85	41.53	12829610	AABA
3	1/6/2006	42.88	43.57	42.80	43.21	29422828	AABA
4	1/9/2006	43.10	43.66	42.82	43.42	16268338	AABA

We have used the 'parse_dates' parameter in the read_csv function to convert the 'Date' column to the DatetimeIndex format.

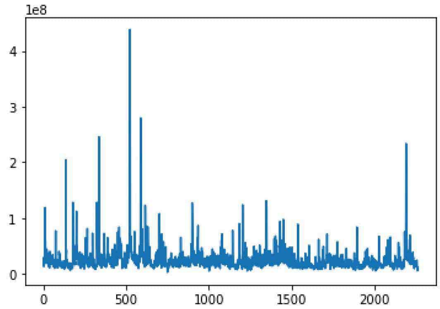
By default, Dates are stored in string format which is not the right format for time series data analysis.

Now, removing the unwanted columns from dataframe i.e. 'Unnamed: 0'.

Example 1: Plotting a simple line plot for time series data.

```
df['Volume'].plot()
```

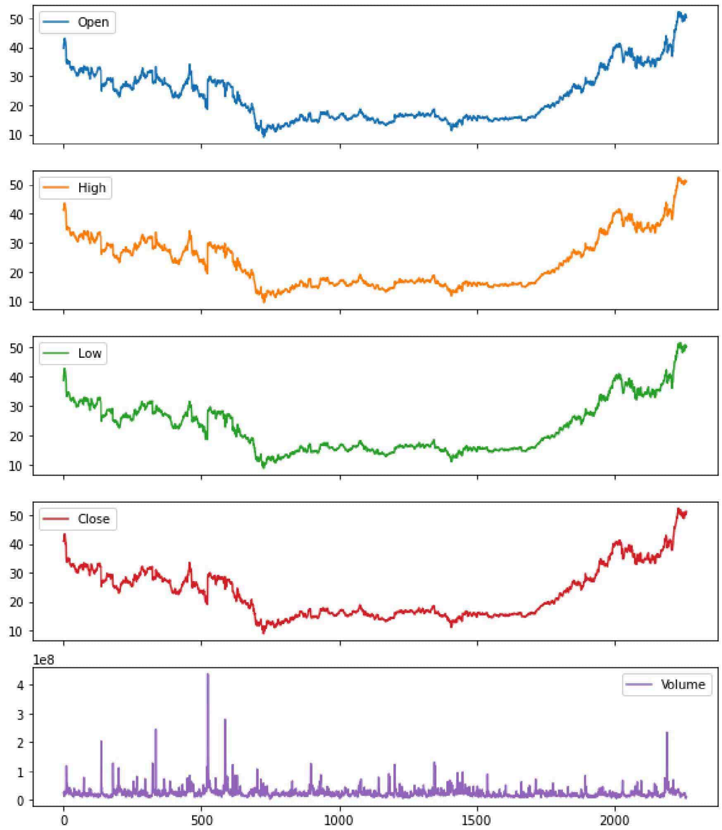
<AxesSubplot:>



Example 2: Now let's plot all other columns using subplot.

```
df.plot(subplots=True, figsize=(10, 12))
```

```
array([<AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>, <AxesSubplot:>,
       <AxesSubplot:>], dtype=object)
```



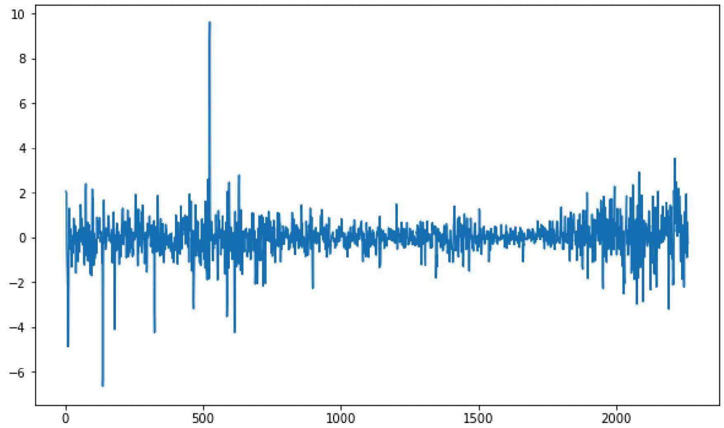
Resampling: Resampling is a methodology of economically using a data sample to improve the accuracy and quantify the uncertainty of a population parameter. Resampling for months or weeks and making bar plots is another very simple and widely used method of finding seasonality. Here we are going to make a bar plot of month data for 2016 and 2017.

Example 3:

Differencing: Differencing is used to make the difference in values of a specified interval. By default, it's one, we can specify different values for plots. It is the most popular method to remove trends in the data.

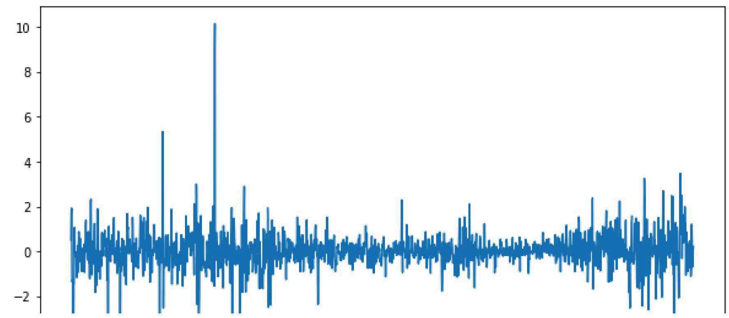
```
df.Low.diff(2).plot(figsize=(10, 6))
```

```
<AxesSubplot:>
```



```
df.High.diff(2).plot(figsize=(10, 6))
```

```
<AxesSubplot:>
```



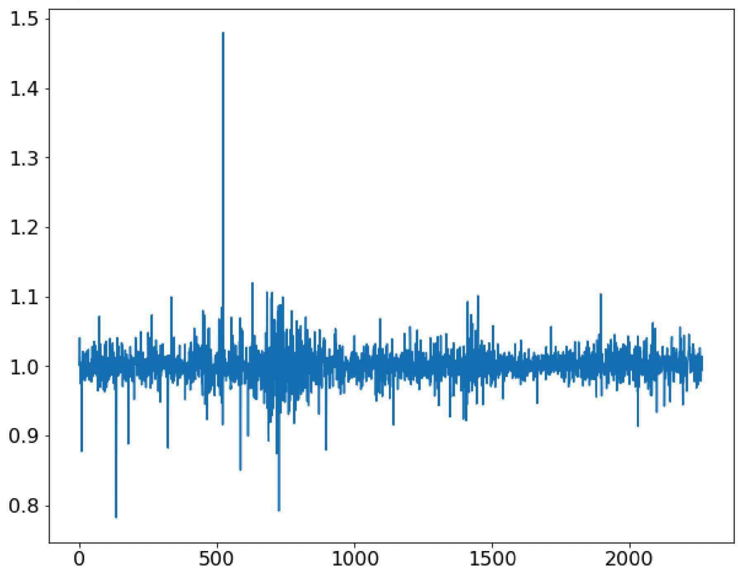
Plotting the Changes in Data

We can also plot the changes that occurred in data over time. There are a few ways to plot changes in data.

Shift: The shift function can be used to shift the data before or after the specified time interval. We can specify the time, and it will shift the data by one day by default. That means we will get the previous day's data. It is helpful to see previous day data and today's data simultaneously side by side.

```
df['Change'] = df.Close.div(df.Close.shift())
df['Change'].plot(figsize=(10, 8), fontsize=16)
```

```
<AxesSubplot:>
```



.div() function helps to fill up the missing data values.

Actually, div() means division.

If we take df. div(6) it will divide each element in df by 6.

We do this to avoid the null or missing values that are created by the 'shift()' operation.

Double-click (or enter) to edit